Experimental streamflow forecasts for Spring 2003

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OUTLINE

Summary of problems with NWP model output

Use of downscaling techniques to compensate for NWP model shortcomings

Experimental hydrologic forecasts

Technology Transfer

MRF FORECAST ARCHIVE

- **The NCEP/NCAR reanalysis –**

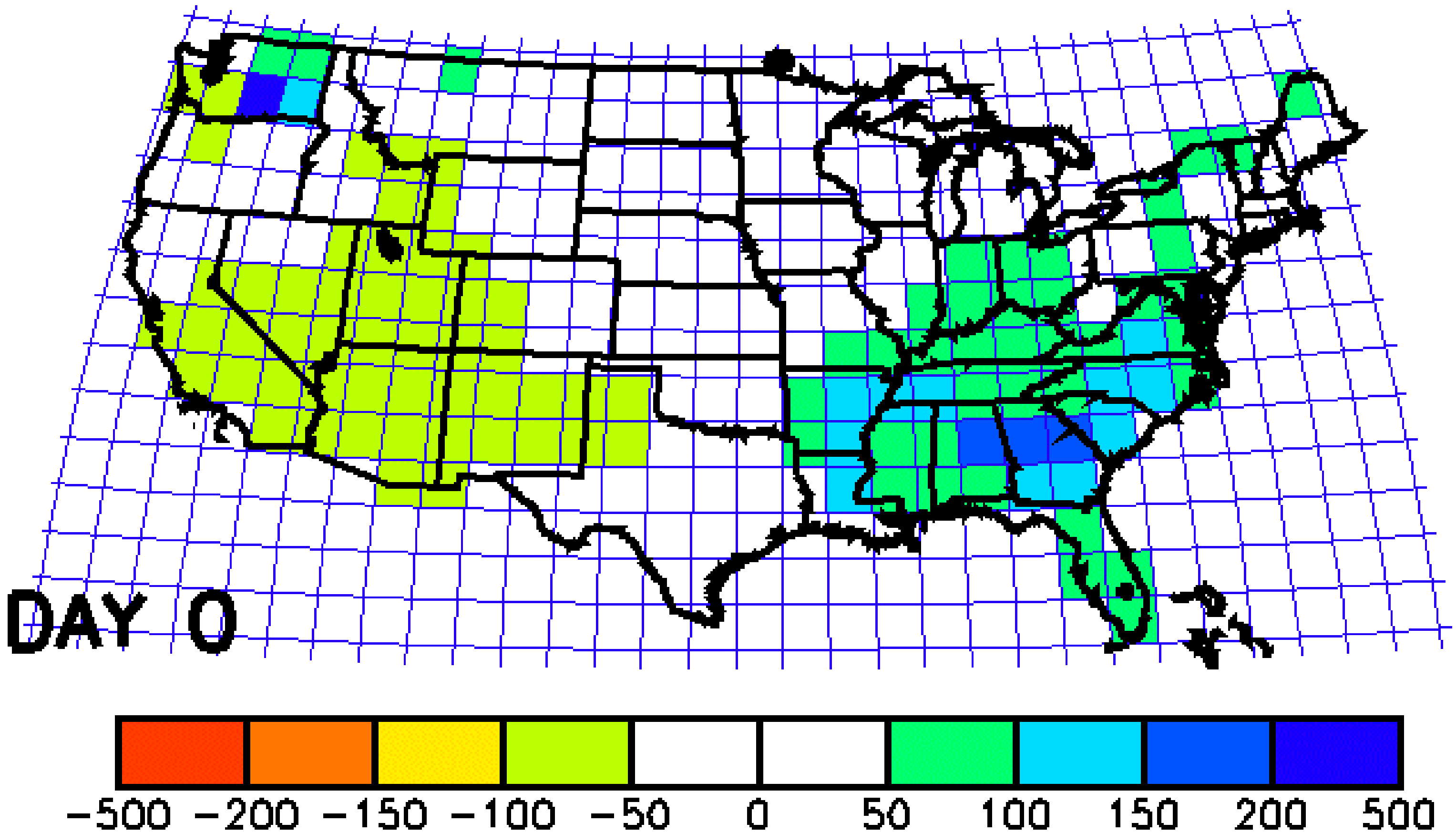
  a 40+ year record of global atmospheric fields and surface fluxes derived from a numerical weather prediction and data assimilation system kept unchanged over the analysis period

- **Every five days, a single realization of an 8-day forecast was run**

  for the period 1958-1998, this provides over 2500 8-day forecasts that can be compared with observations

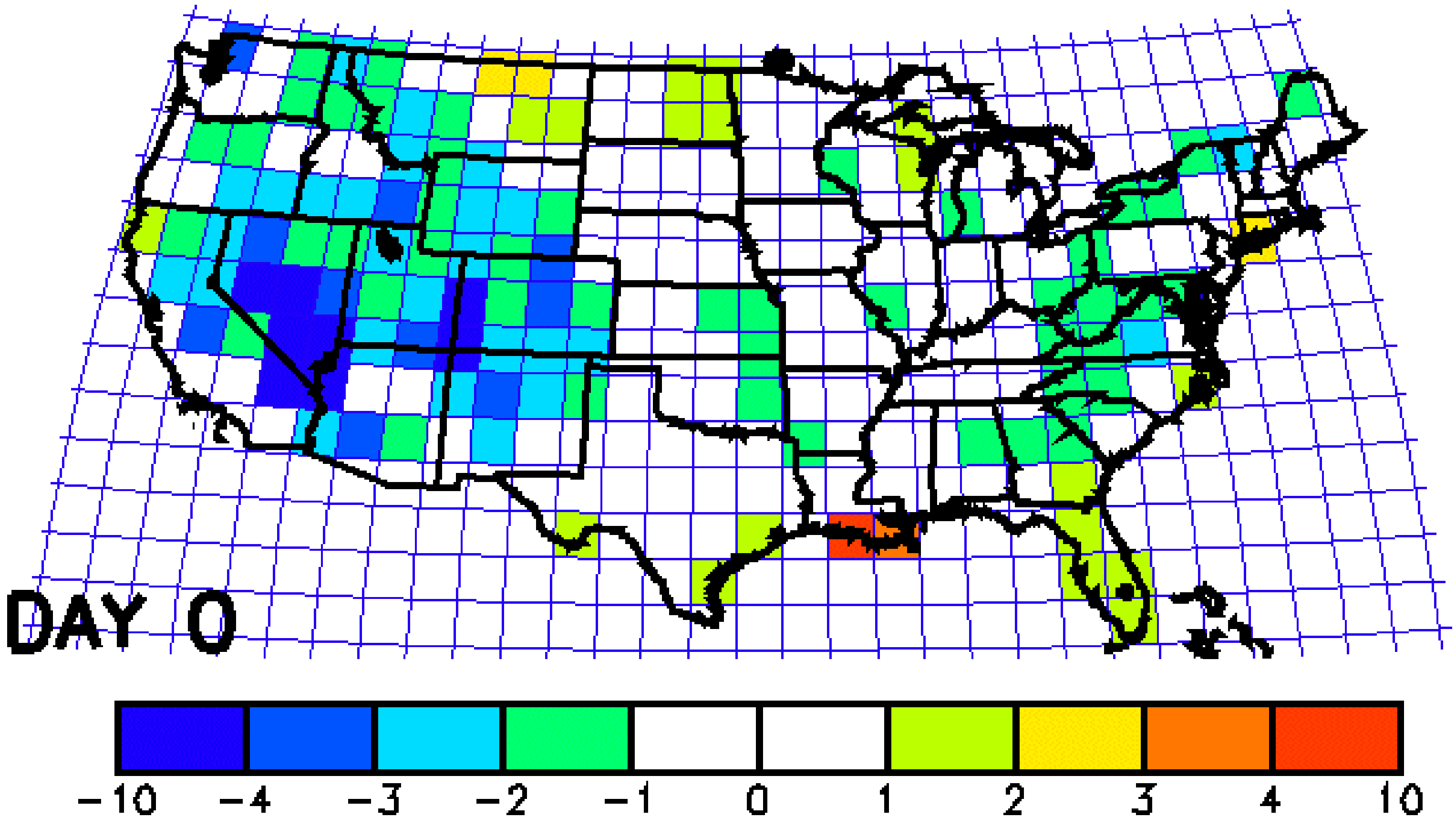
- **Model output is archived on a regular lat/lon grid with approx 1.875º horizontal resolution.**

PRECIPITATION BIASES



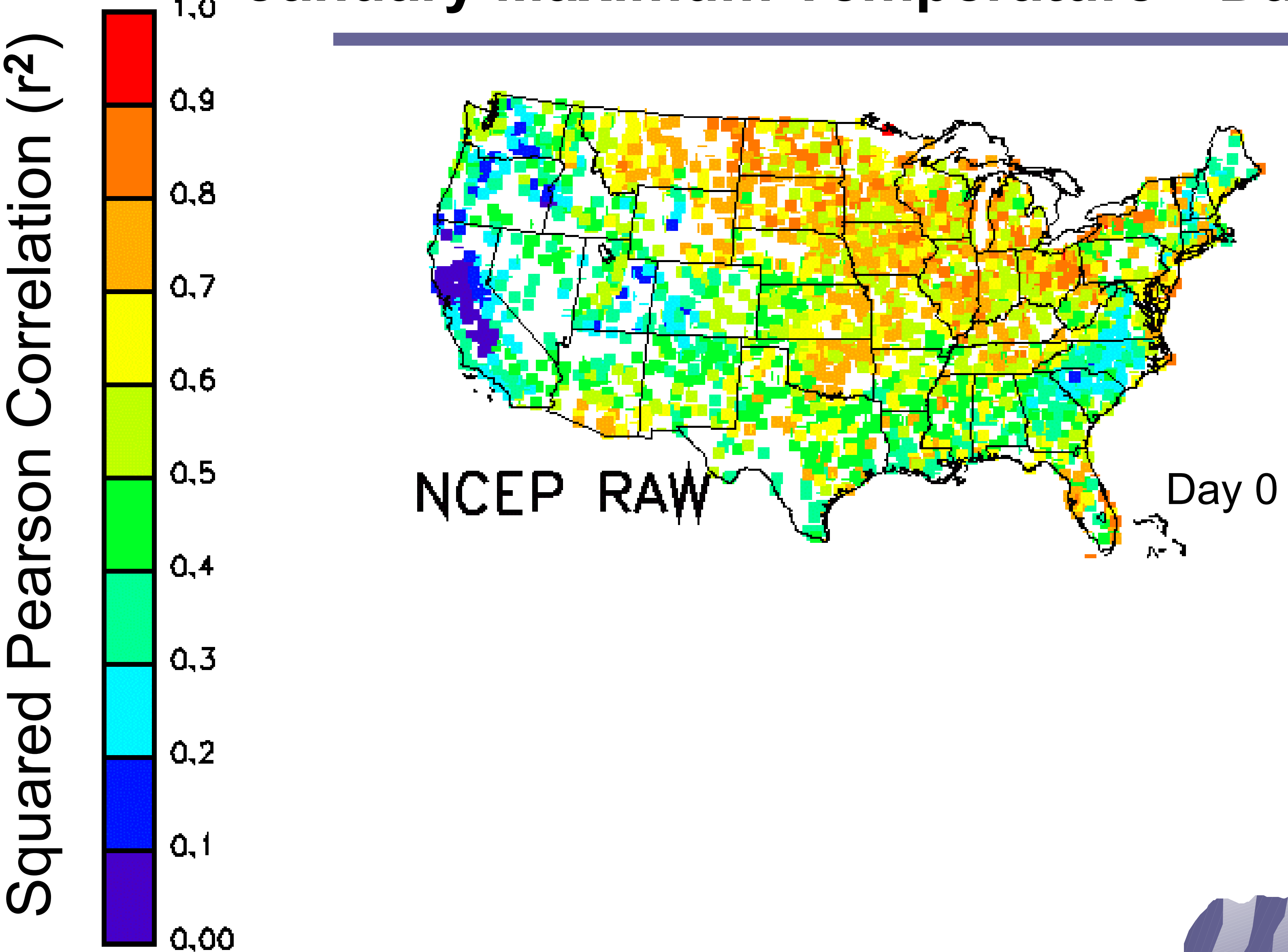
Precipitation biases are in excess of 100% of the mean

TEMPERATURE BIASES

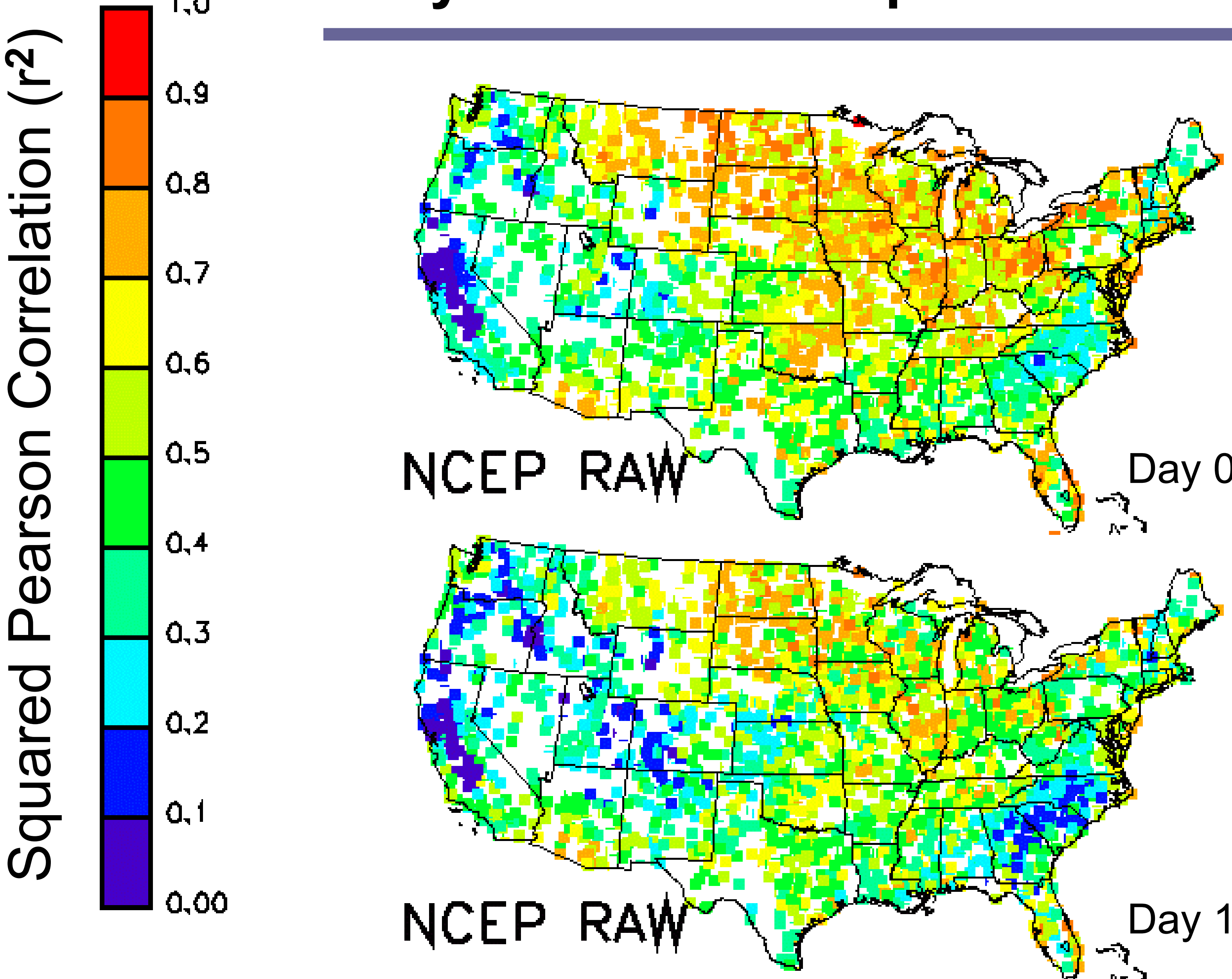


Temperature biases are in excess of 3°C

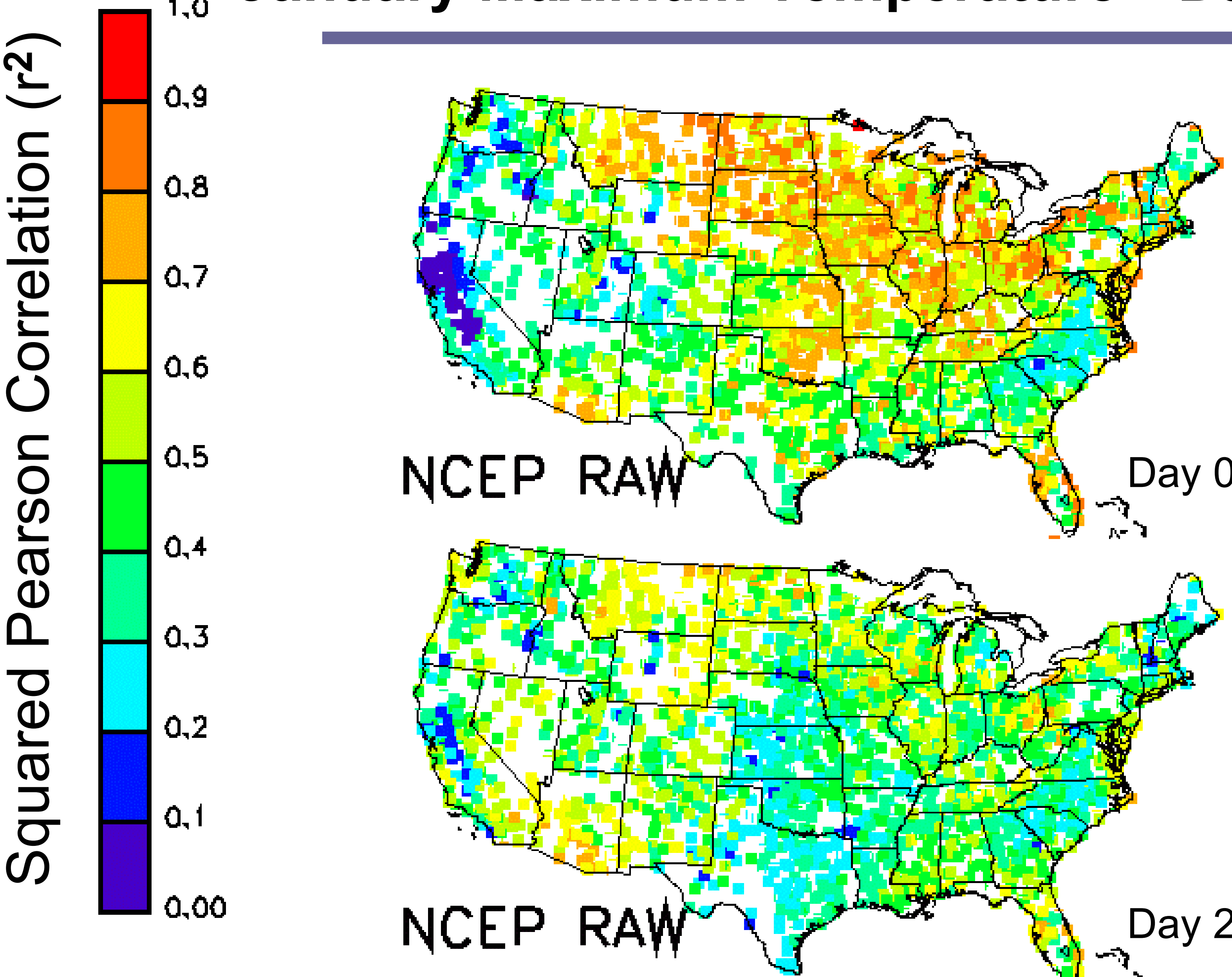
January Maximum Temperature—Day 0



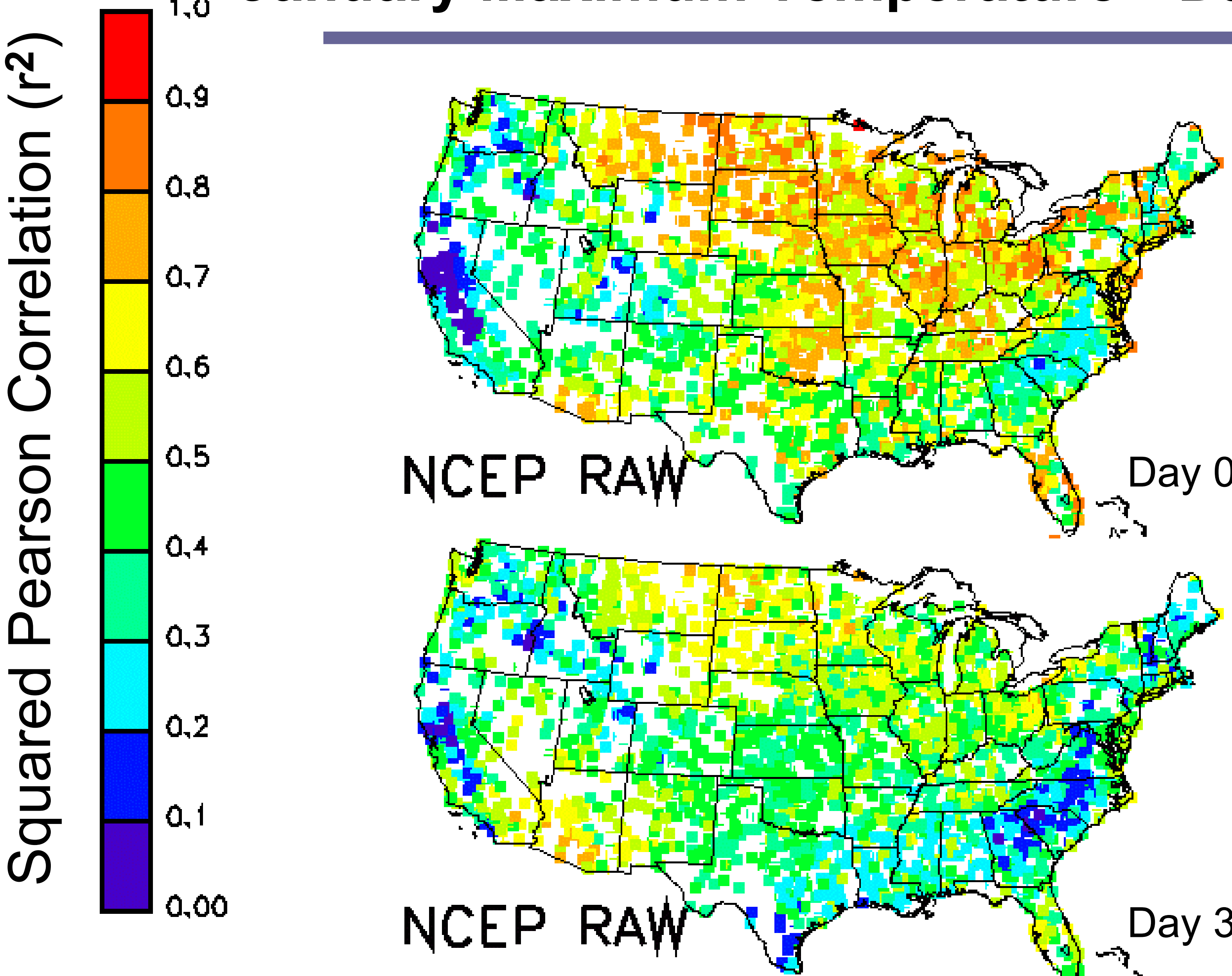
January Maximum Temperature—Day 1



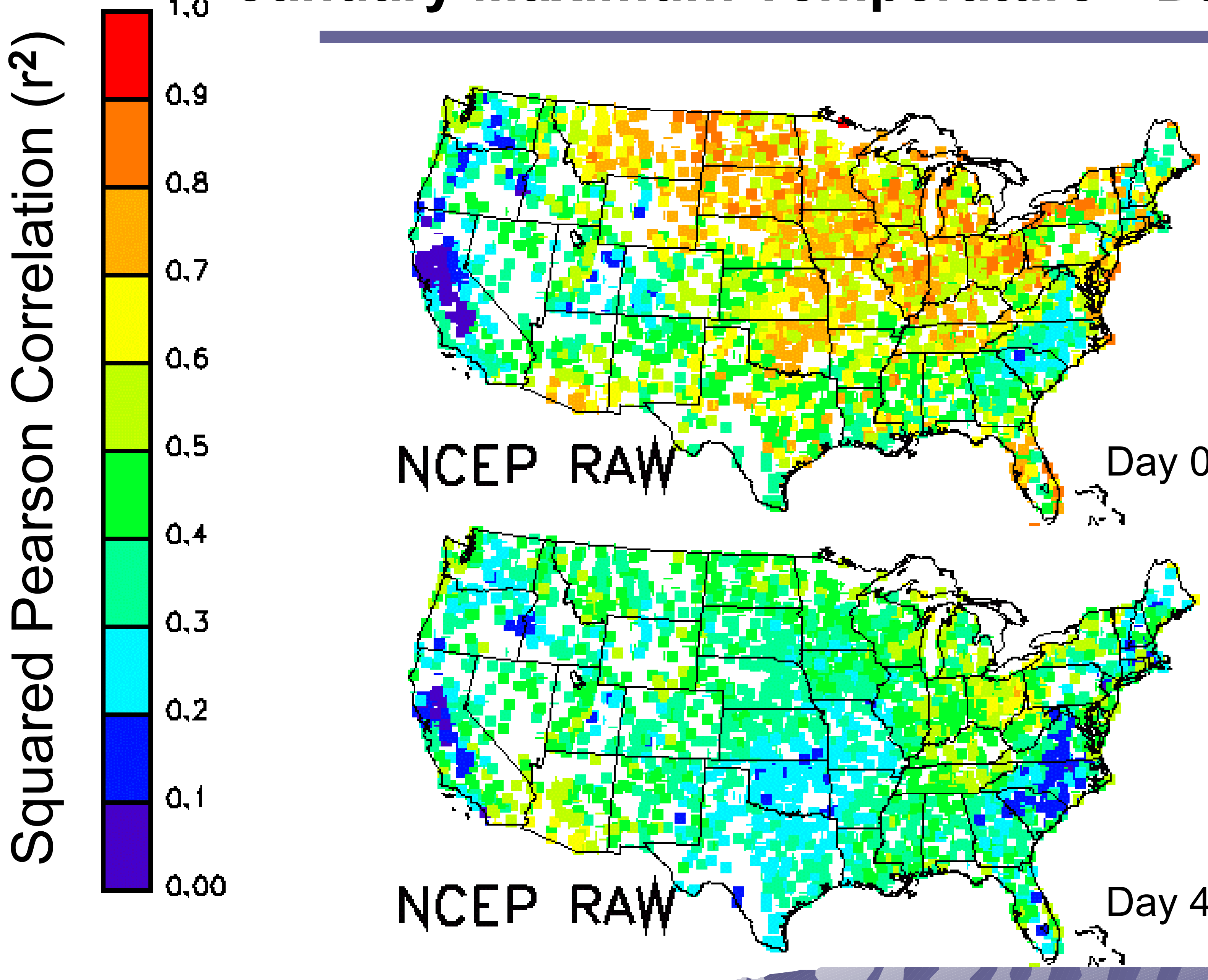
January Maximum Temperature—Day 2



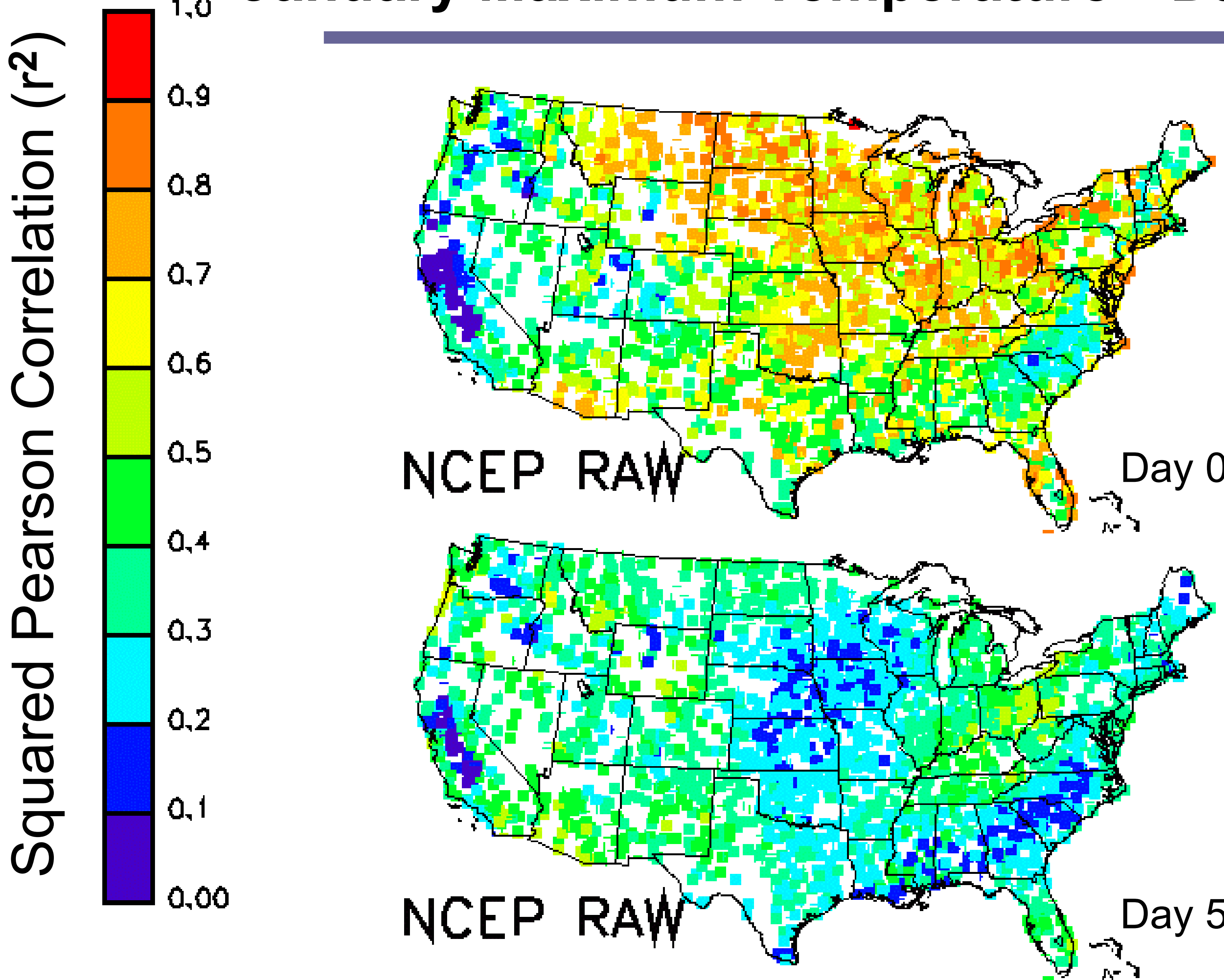
January Maximum Temperature—Day 3



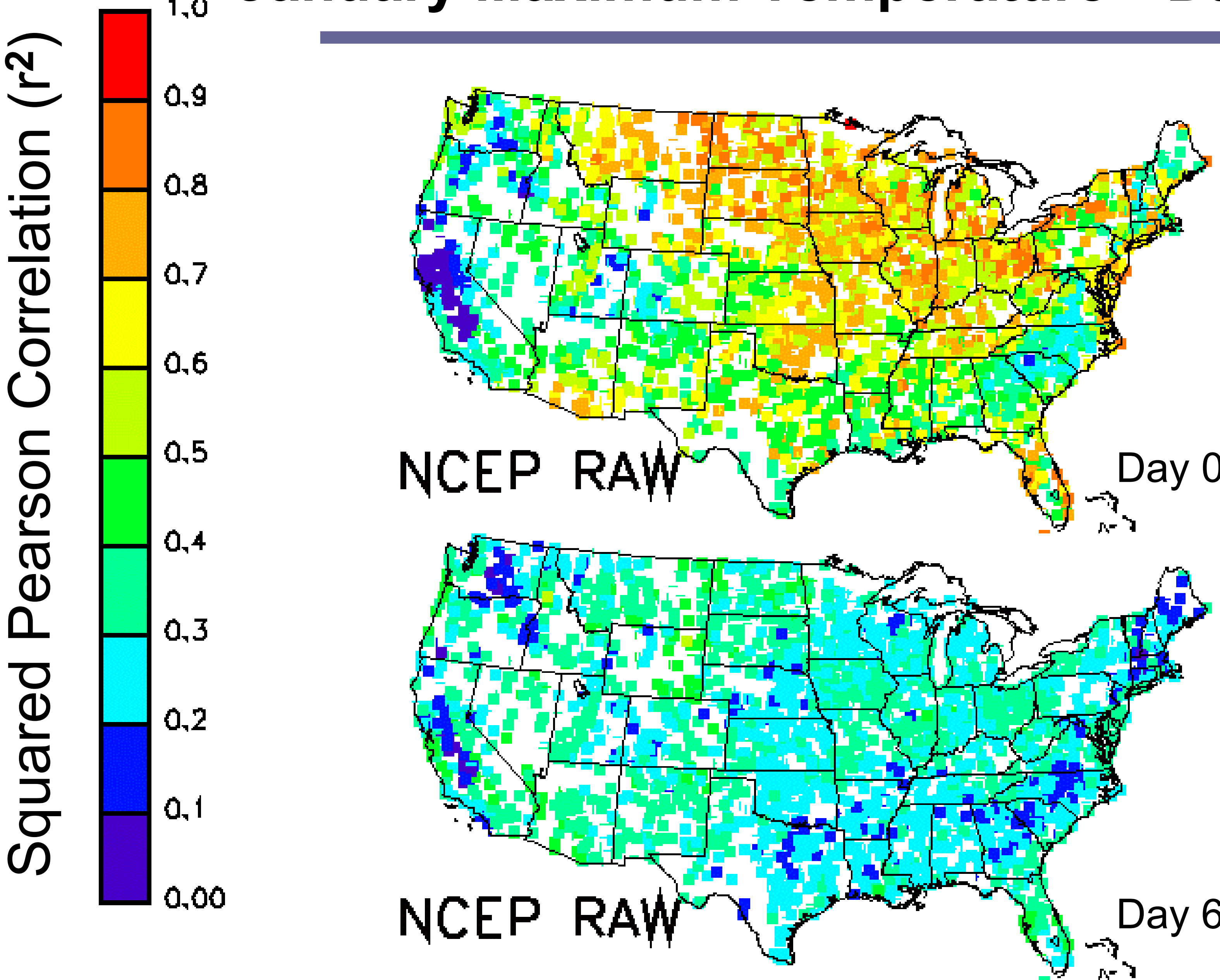
January Maximum Temperature—Day 4



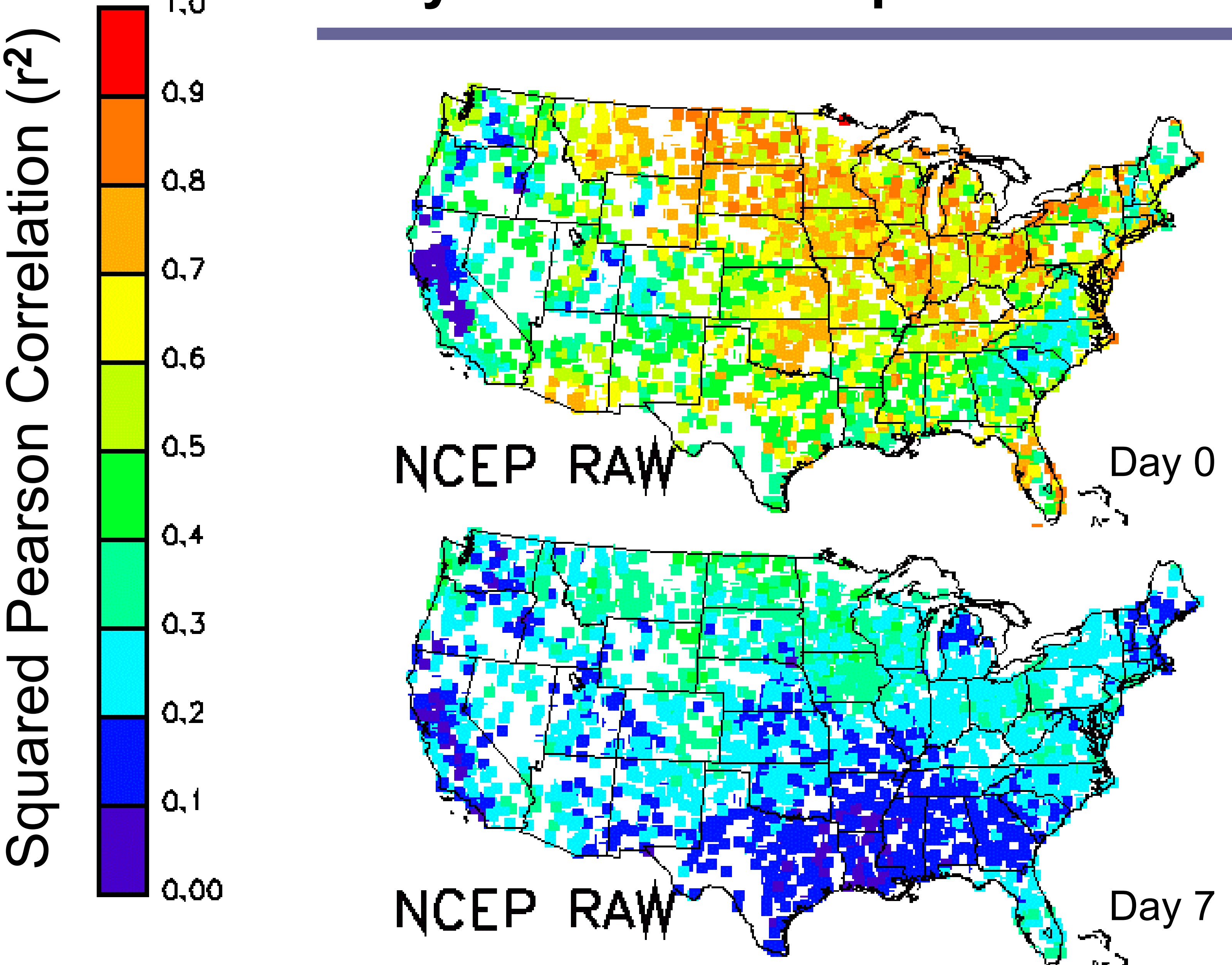
January Maximum Temperature—Day 5



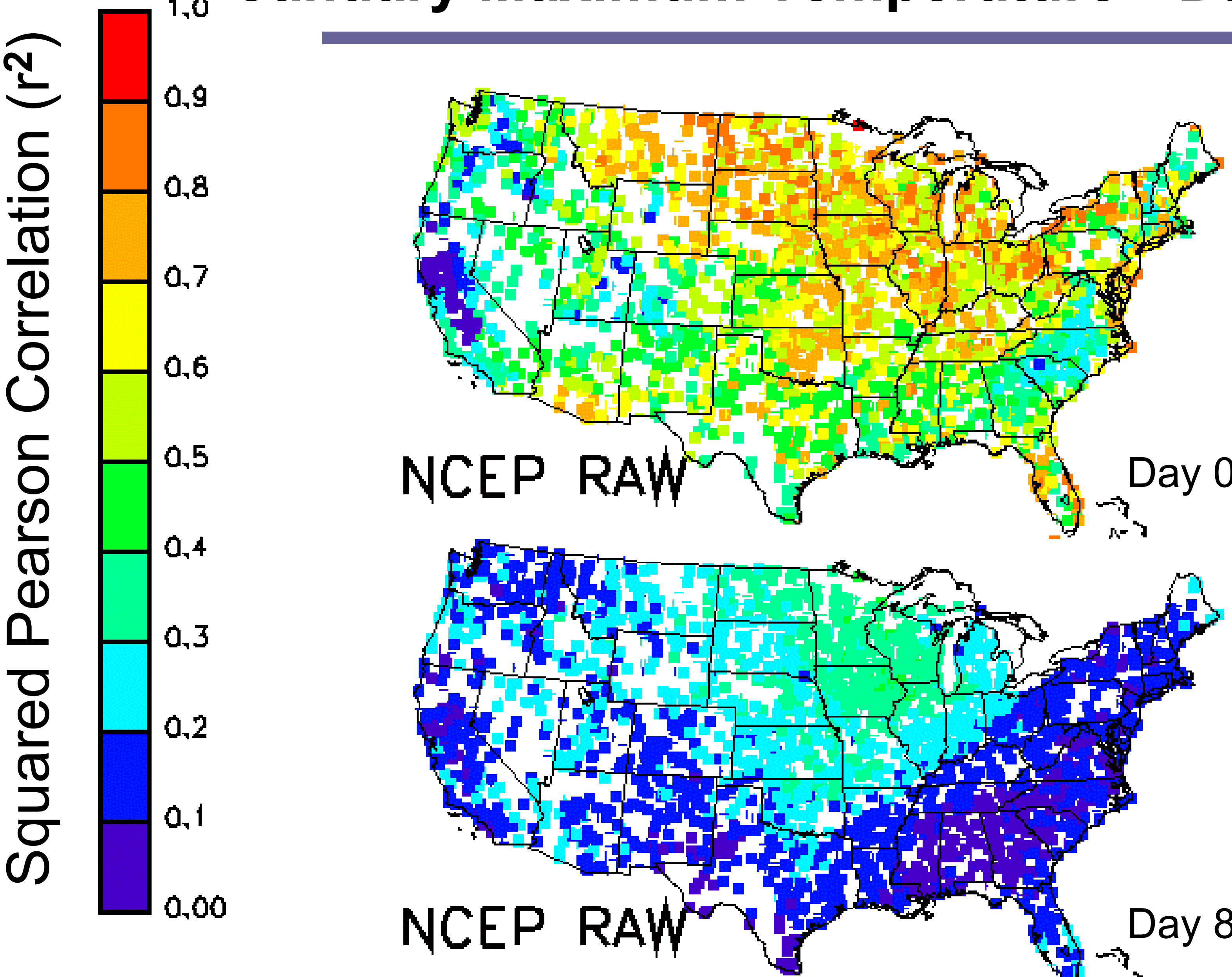
January Maximum Temperature—Day 6



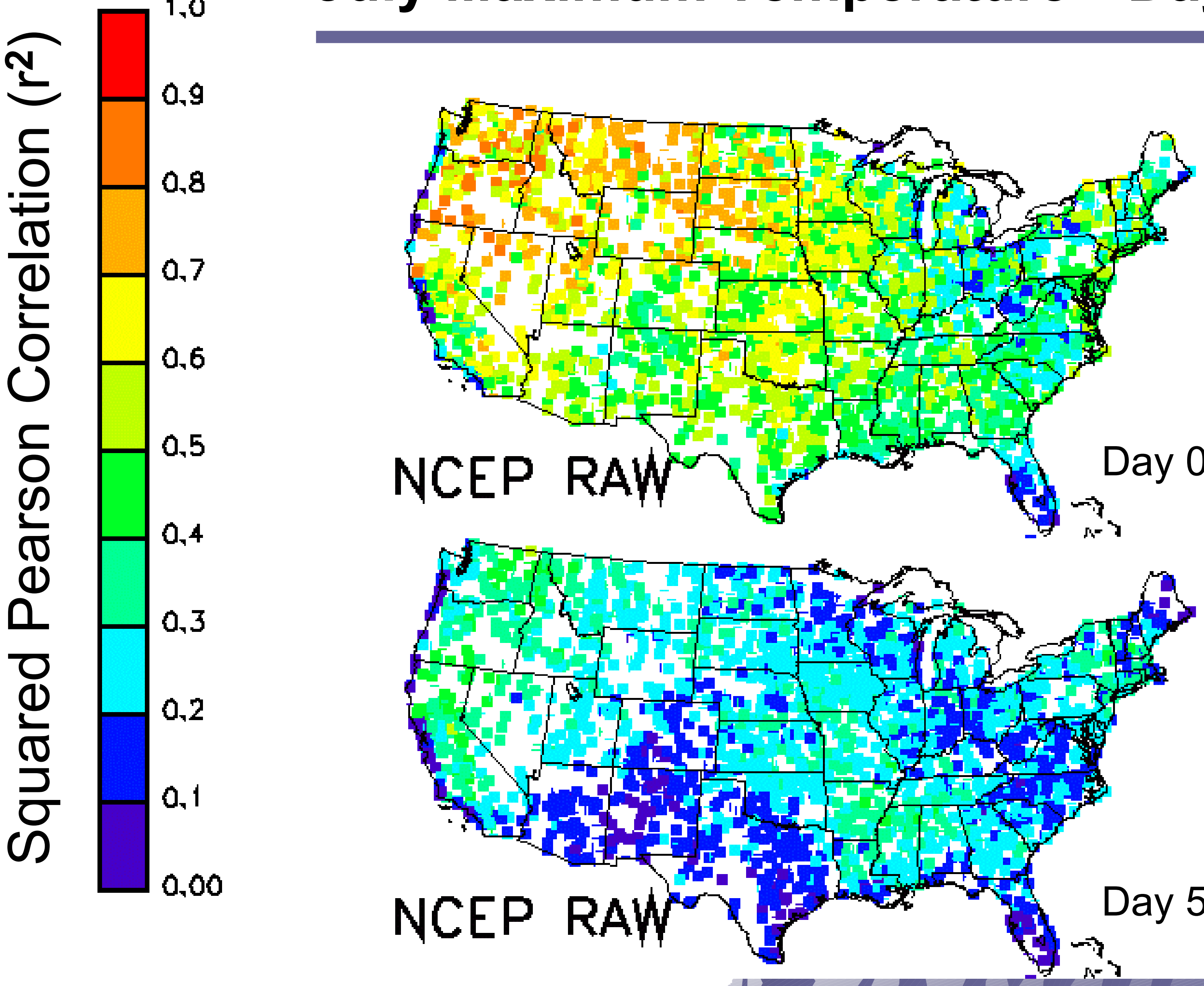
January Maximum Temperature—Day 7



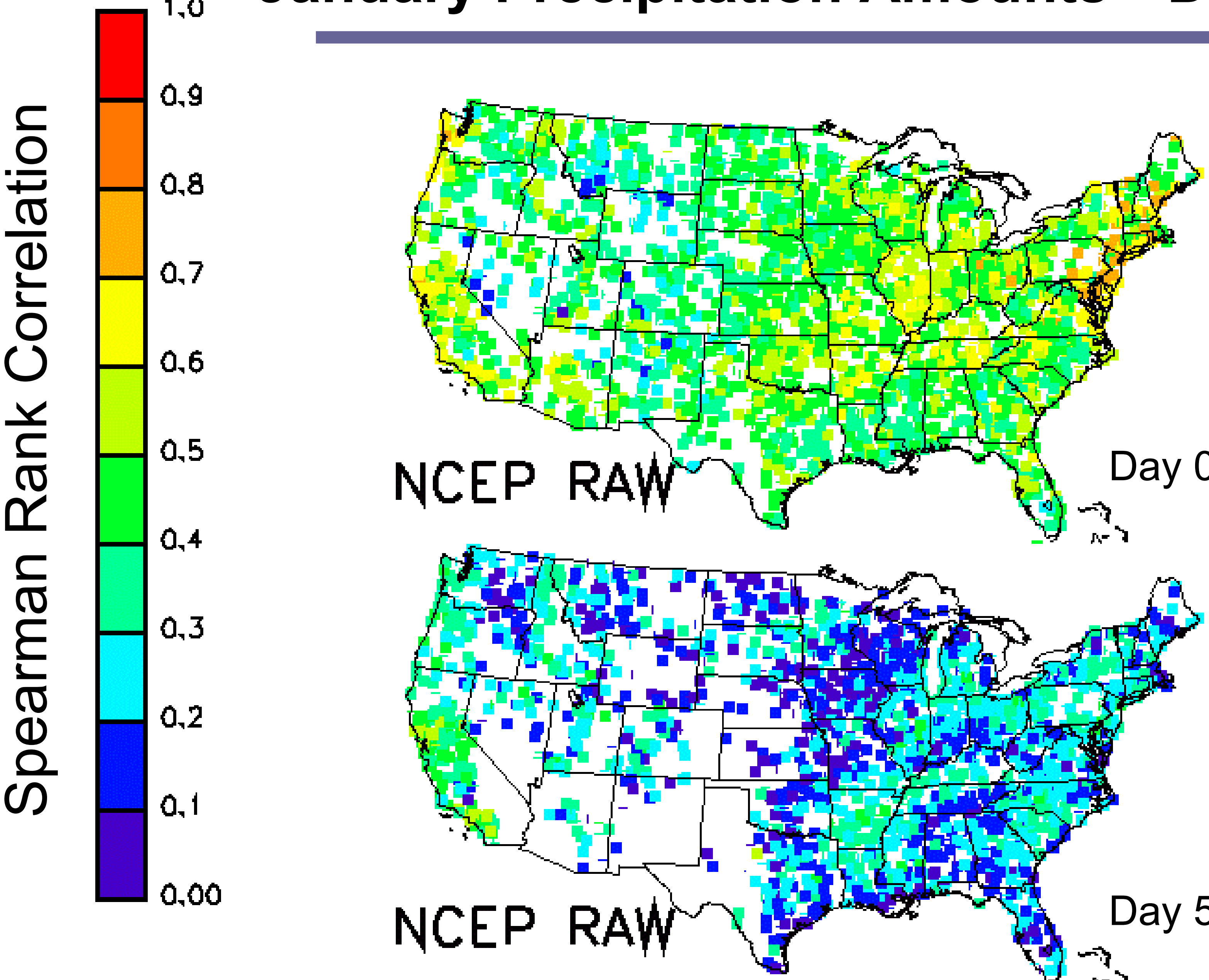
January Maximum Temperature—Day 8



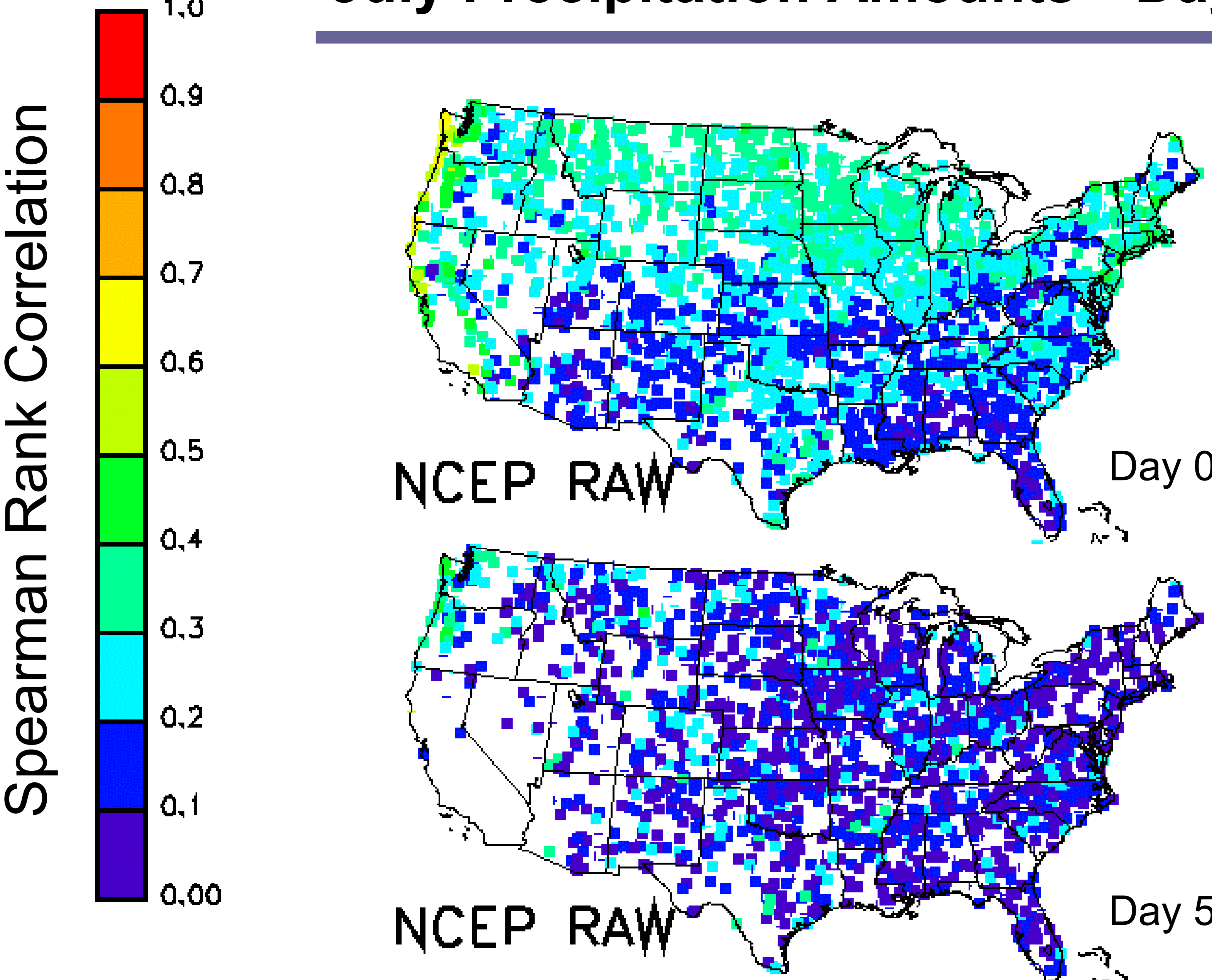
July Maximum Temperature—Day 5



January Precipitation Amounts—Day 5

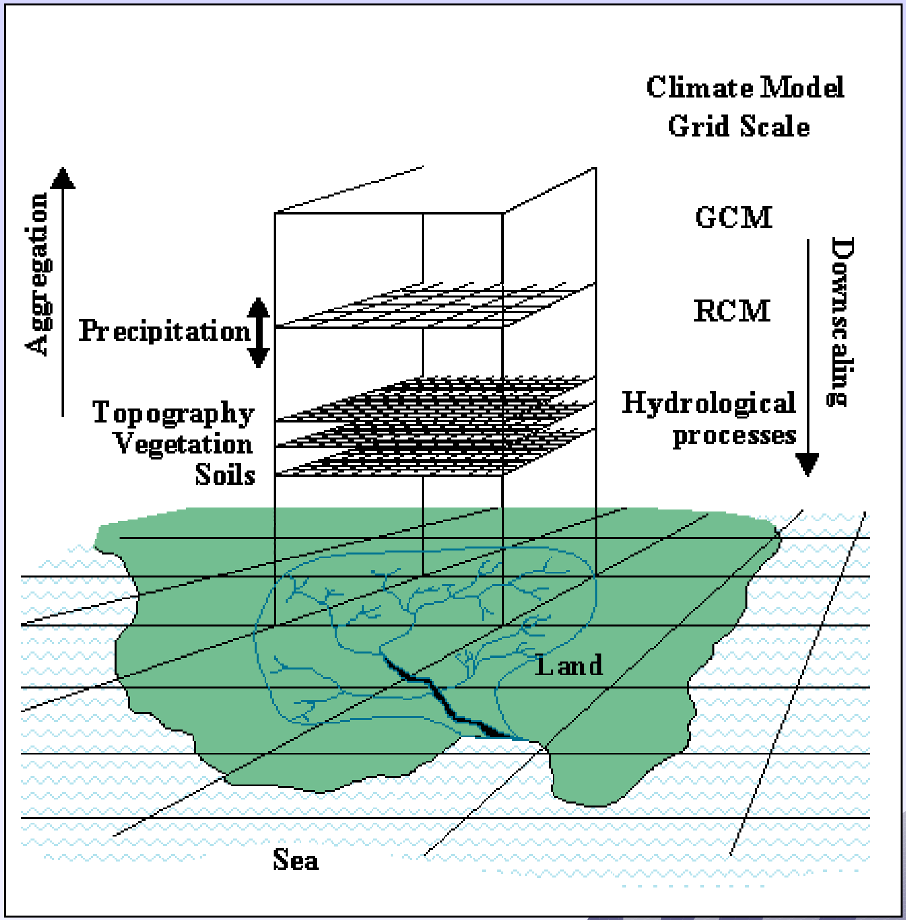


July Precipitation Amounts—Day 5



DOWNSCALING OF THE NCEP MRF OUTPUT

- **Use Multiple linear Regression with forward selection**
- **Predictor Variables (over 300):**
  - Geo-potential height, wind, and humidity at five pressure levels
  - Various surface flux variables
  - Computed variables such as vorticity advection, stabilitiy indices, etc.
  - Variables lagged to account for temporal phase errors in atmospheric forecasts.
- **Predictands are maximum and minimum temperature, precipitation occurrence, and precipitation amounts**



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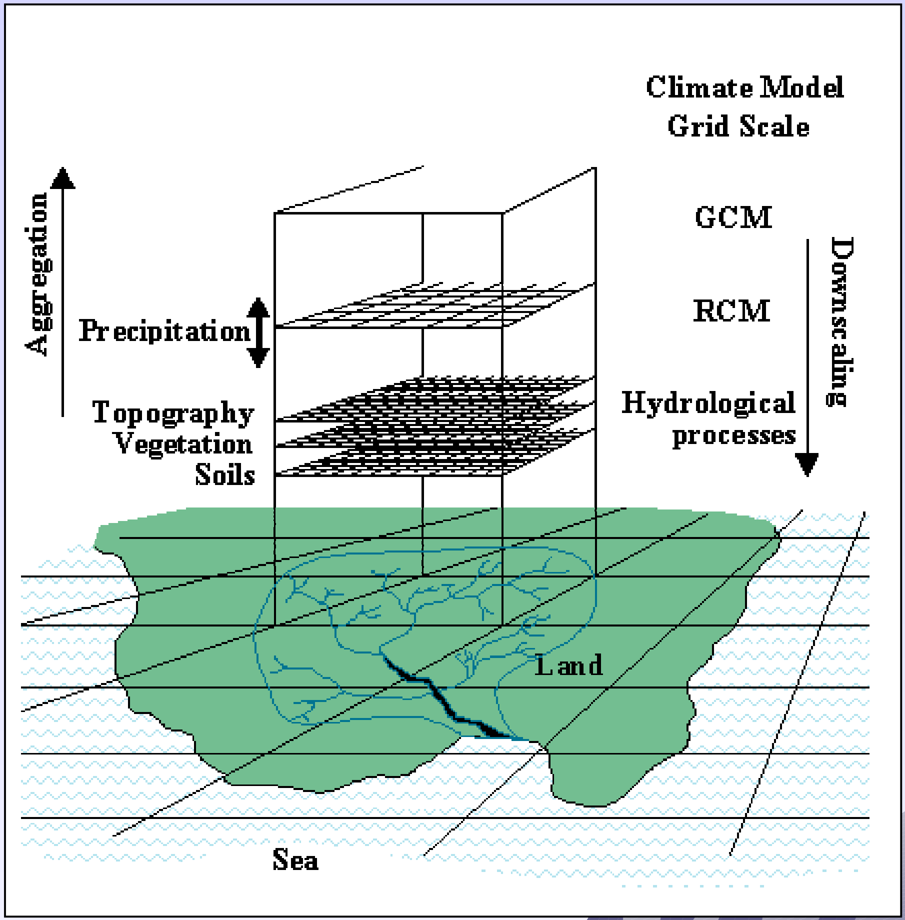
- **Predictands are maximum and minimum temperature, precipitation occurrence, and precipitation amounts**
- **Use cross-validation procedures for variable selection – typically less than 8 variables are selected for a given equation**
- **Stochastic modeling of the residuals in the regression equation to provide ensemble time series**



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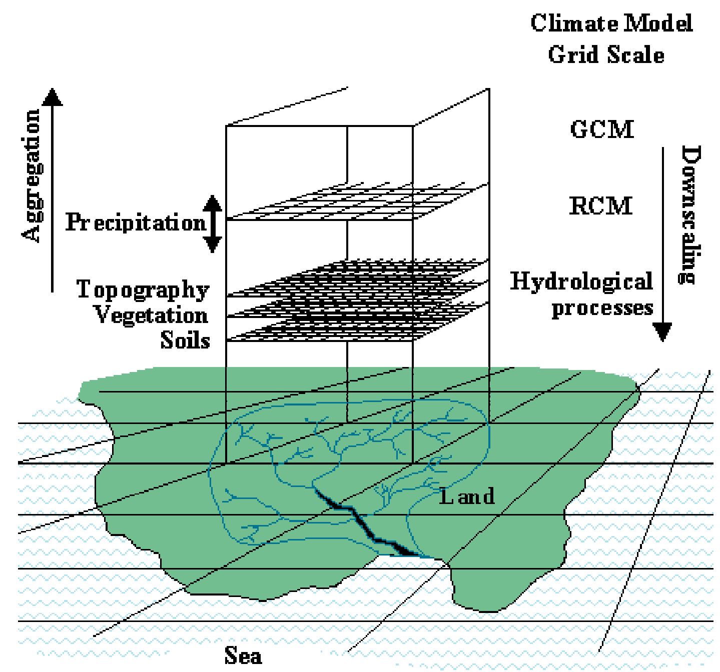
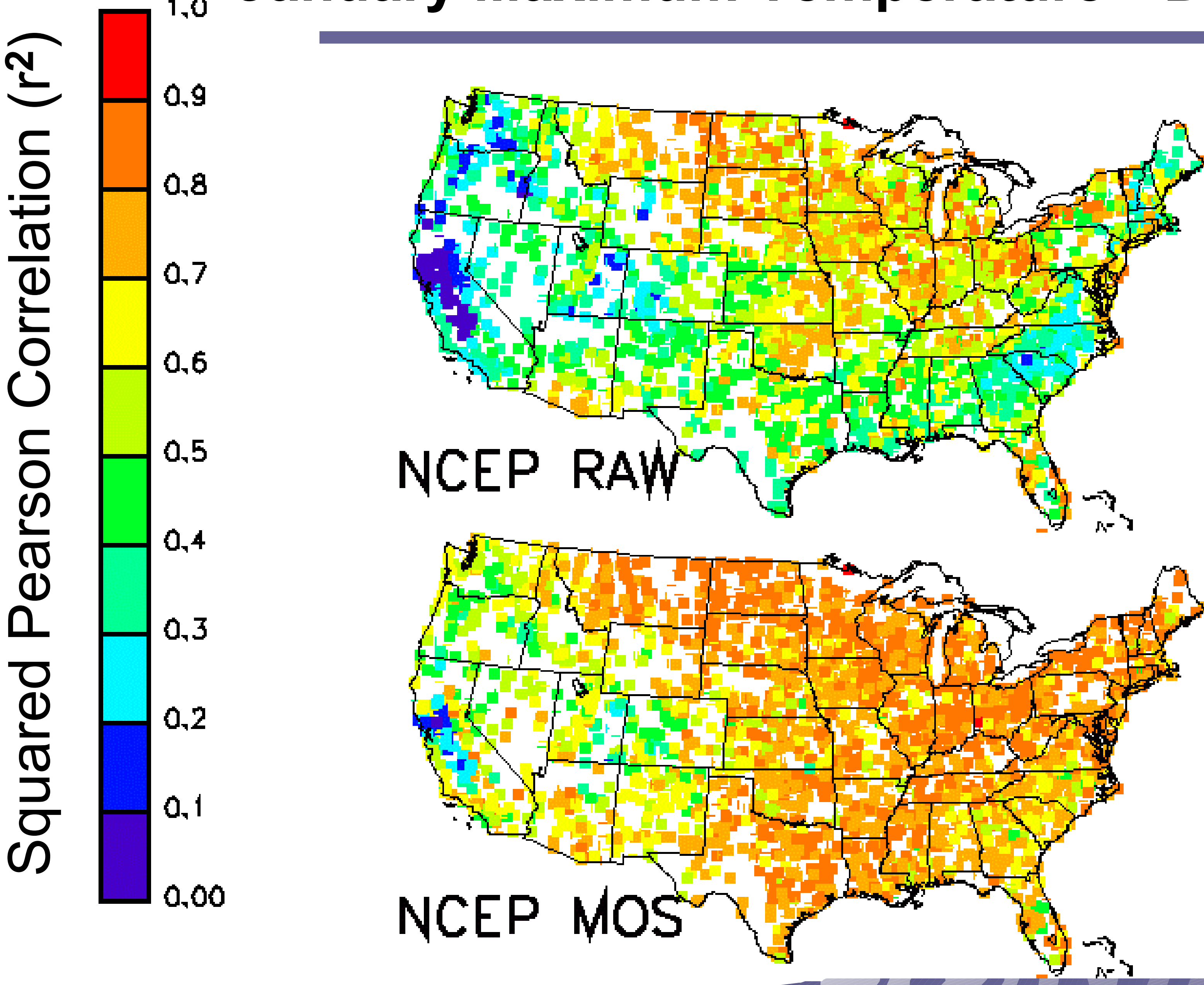
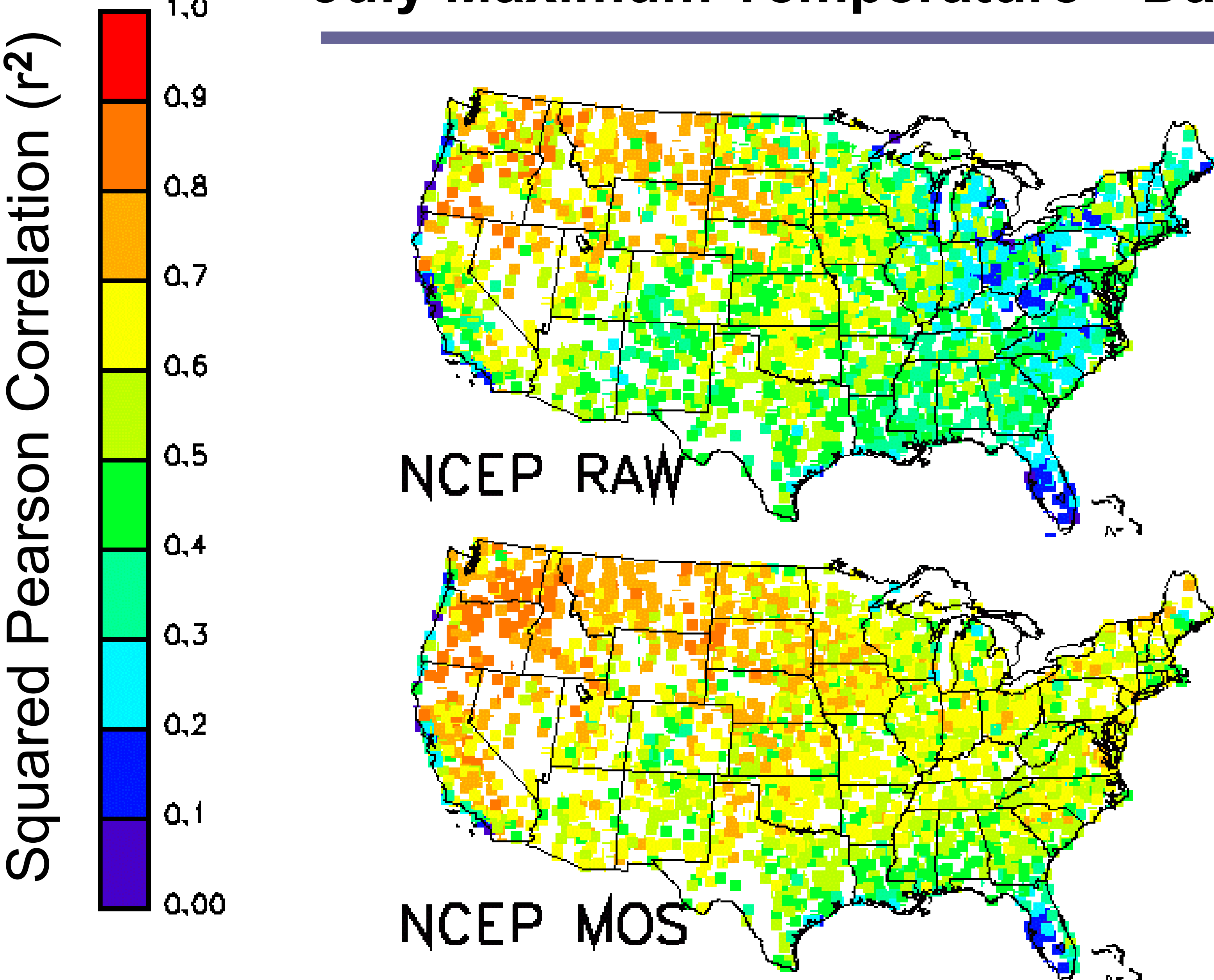


- A separate equation is developed for each station, each forecast day, and each month.
- Equations developed over the period 1958-1976, and validated for the period 1977-1998.

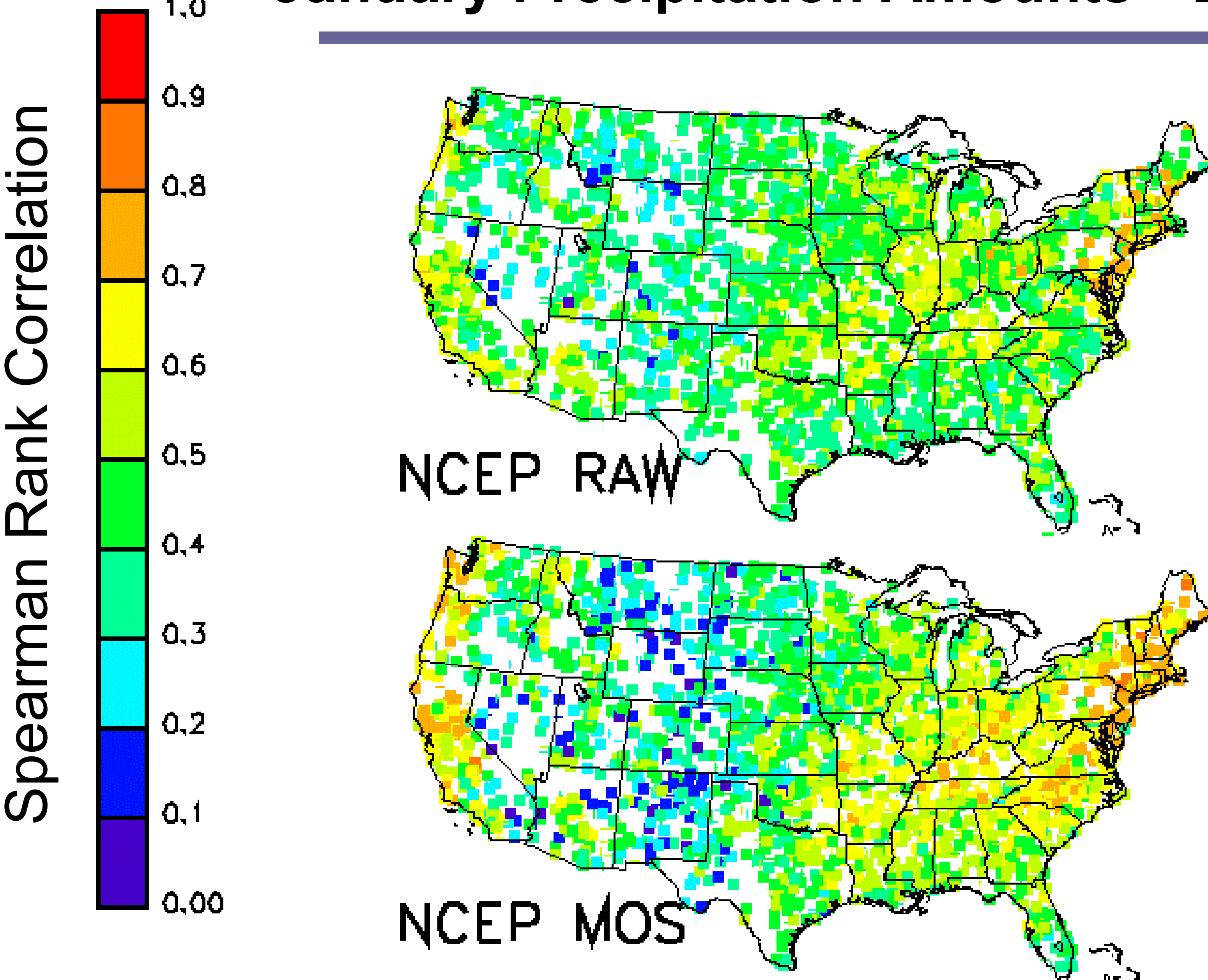
January Maximum Temperature—Day 0



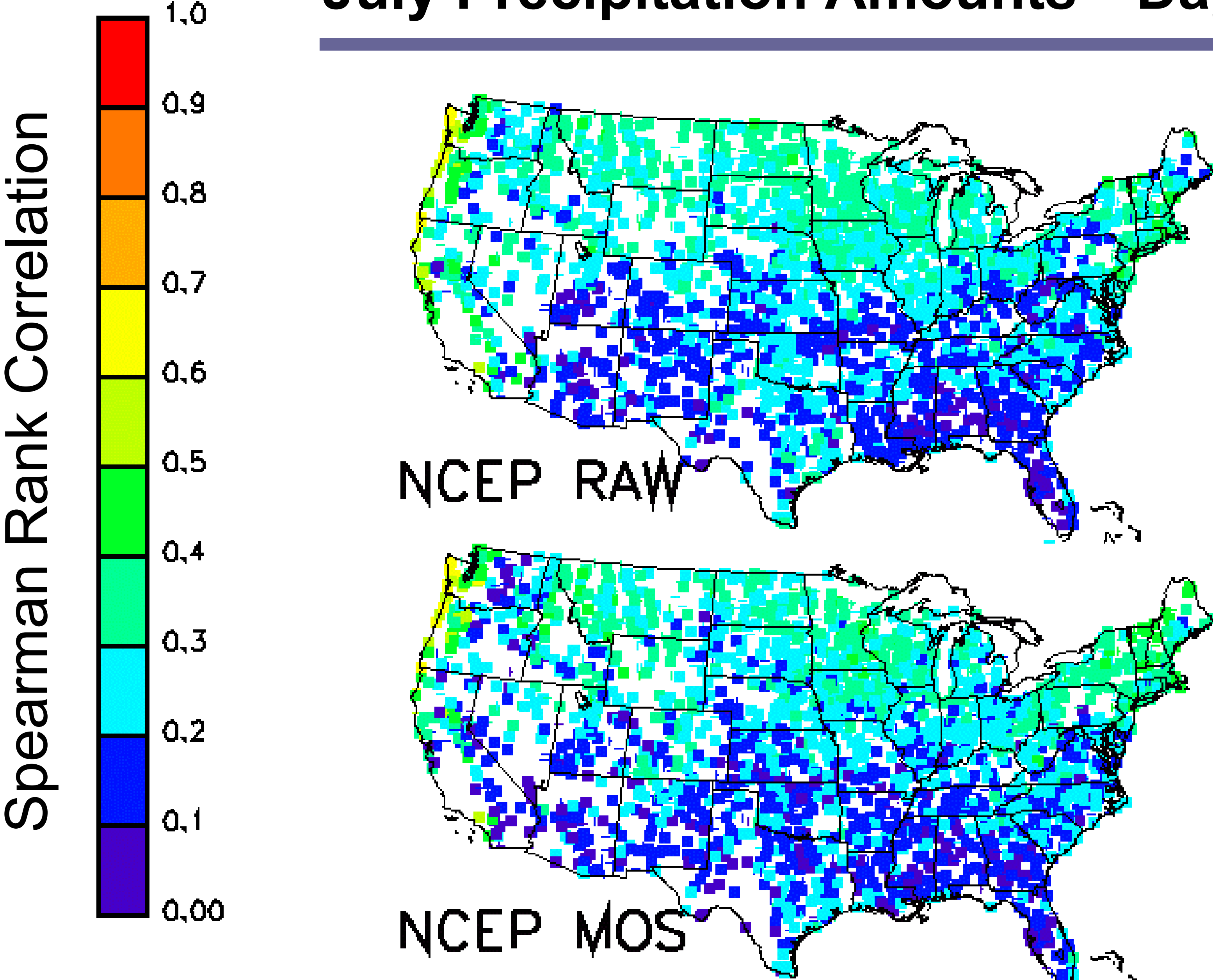
July Maximum Temperature—Day 0



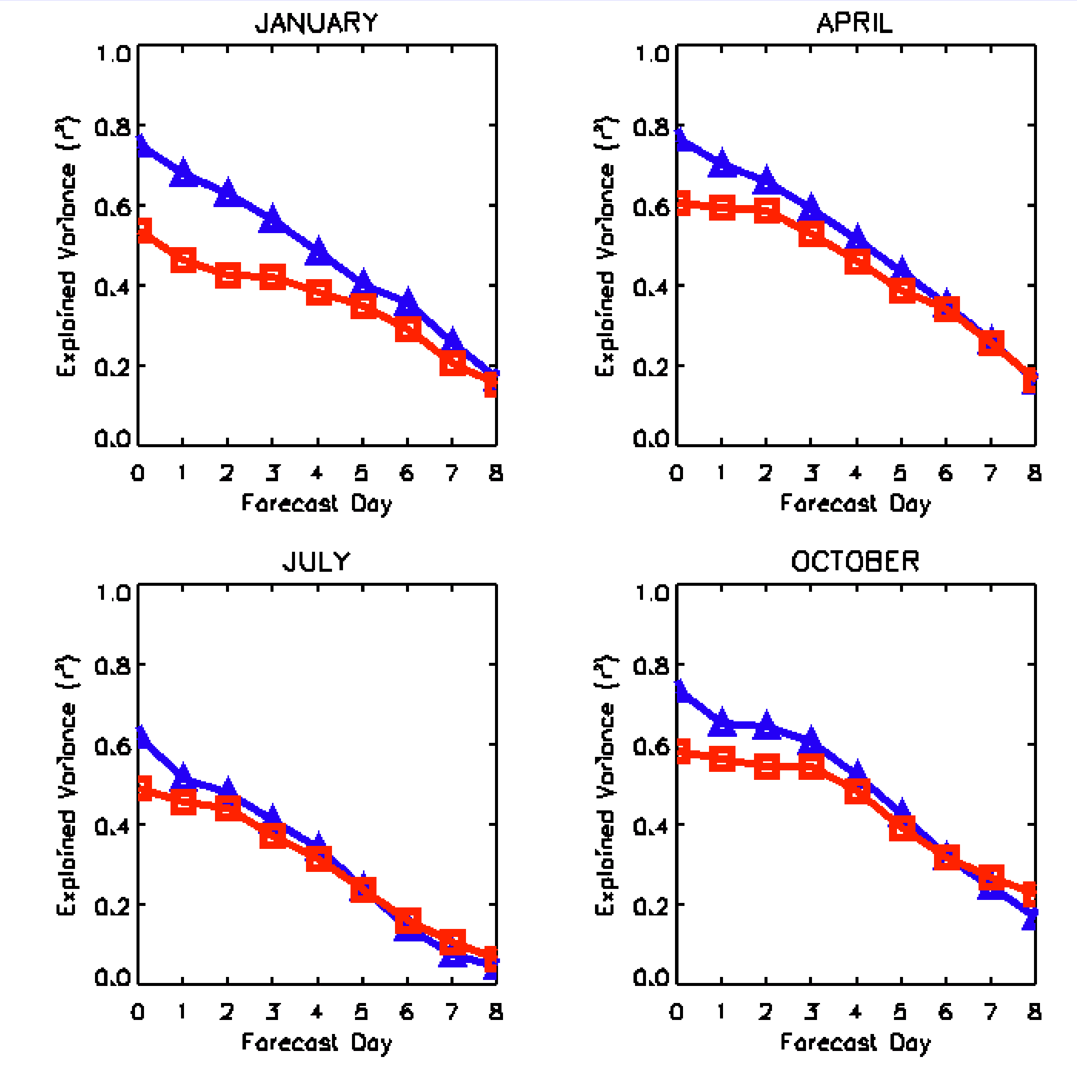
January Precipitation Amounts—Day 0



July Precipitation Amounts—Day 0

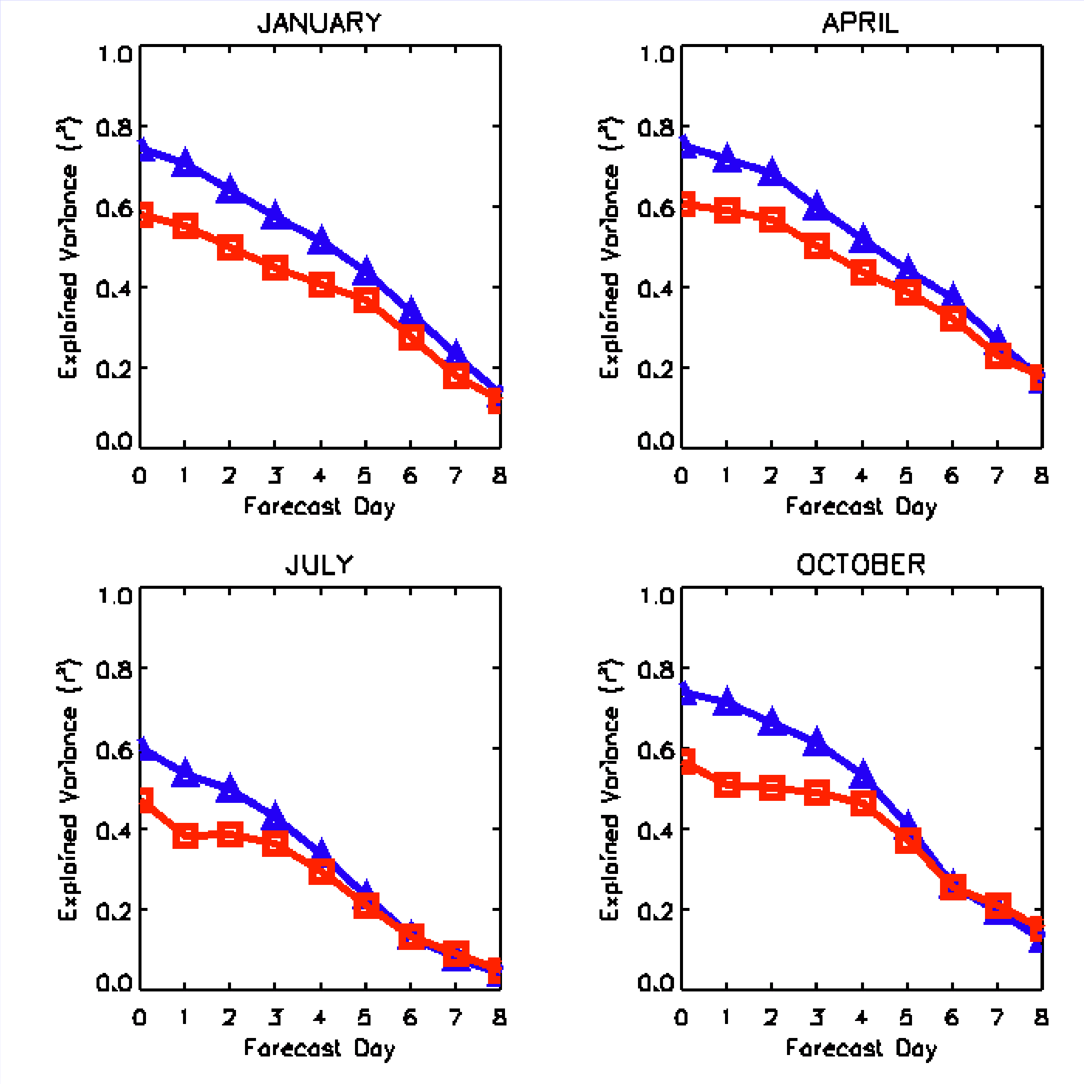


SKILL OF MAXIMUM TEMPERATURE PREDICTIONS



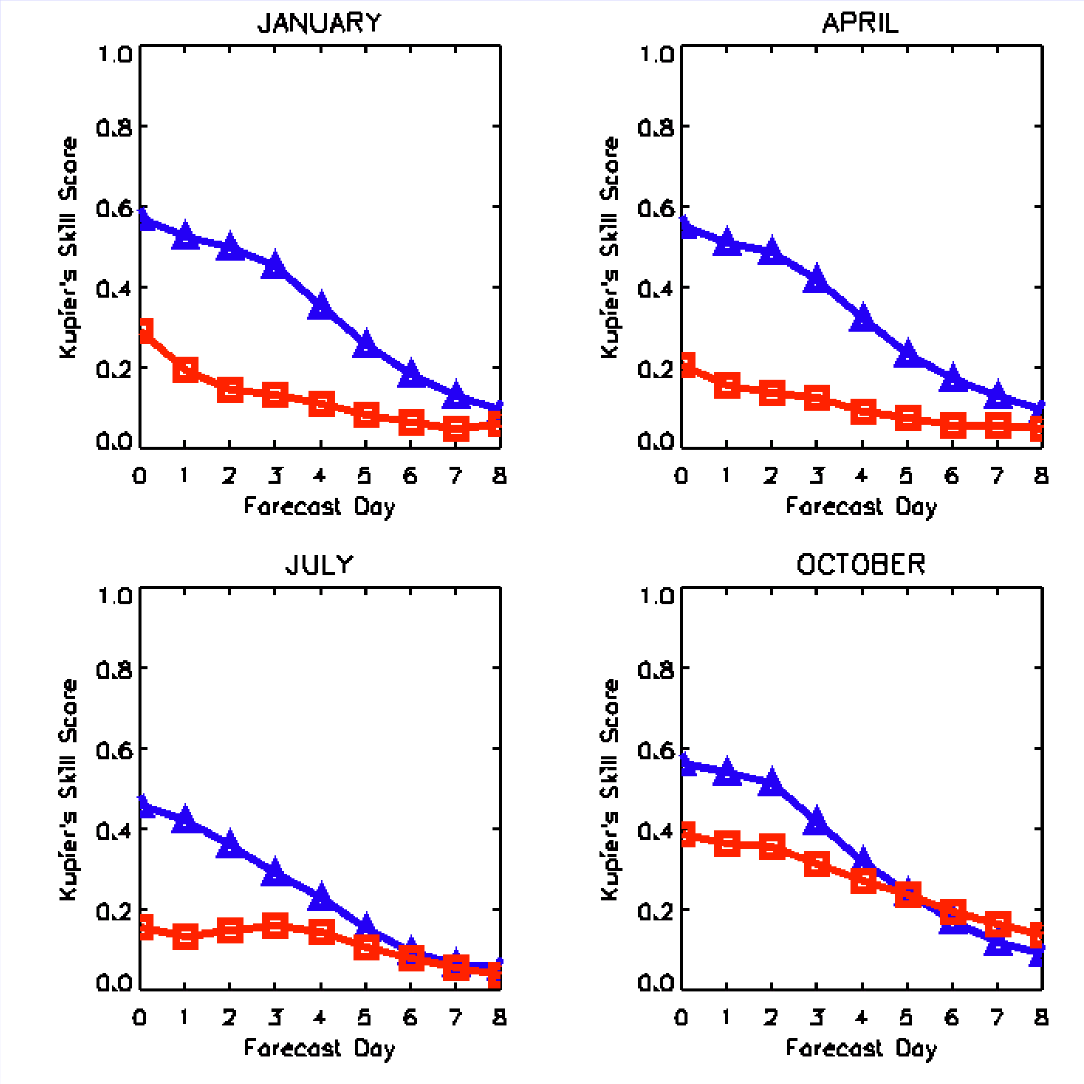
- Median explained variance of maximum temperature predictions, computed for the 11,000 NWS co-op stations.
- Red is raw NCEP predictions, blue is based on MOS guidance.

SKILL OF MINIMUM TEMPERATURE PREDICTIONS



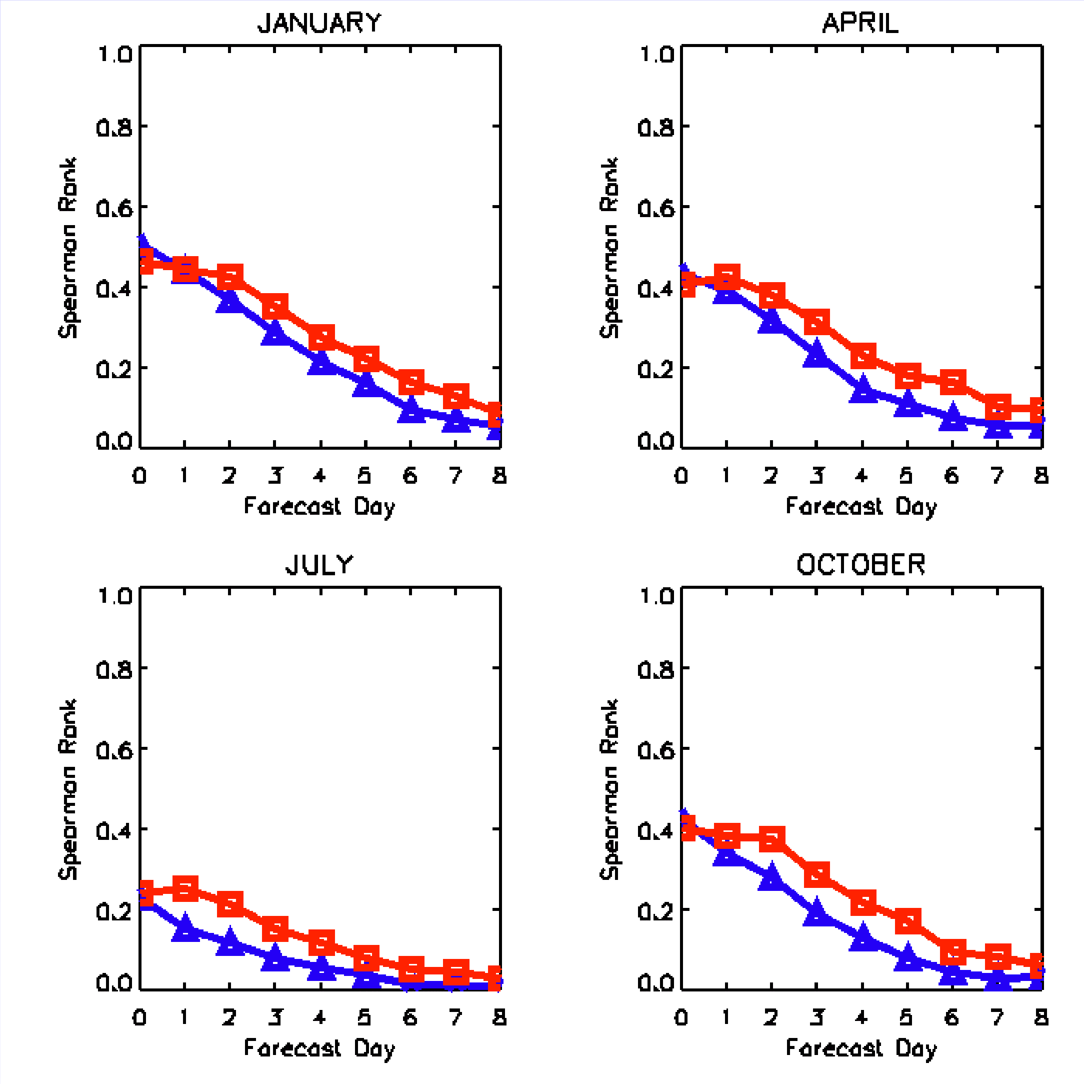
- Median explained variance of minimum temperature predictions, computed for the 11,000 NWS co-op stations.
- Red is raw NCEP predictions, blue is based on MOS guidance.

SKILL OF PRECIP OCCURRENCE PREDICTIONS



- ❑ Median explained variance of precipitation occurrence predictions, computed for the 11,000 NWS co-op stations.
- ❑ Red is raw NCEP predictions, blue is based on MOS guidance.

SKILL OF PRECIPITATION PREDICTIONS



- ❑ Median explained variance of precipitation predictions, computed for the 11,000 NWS co-op stations.
- ❑ Red is raw NCEP predictions, blue is based on MOS guidance.

BASINS

Compare ESP and SDS 9-day forecasts of runoff every 5 days

Hydrologic Model

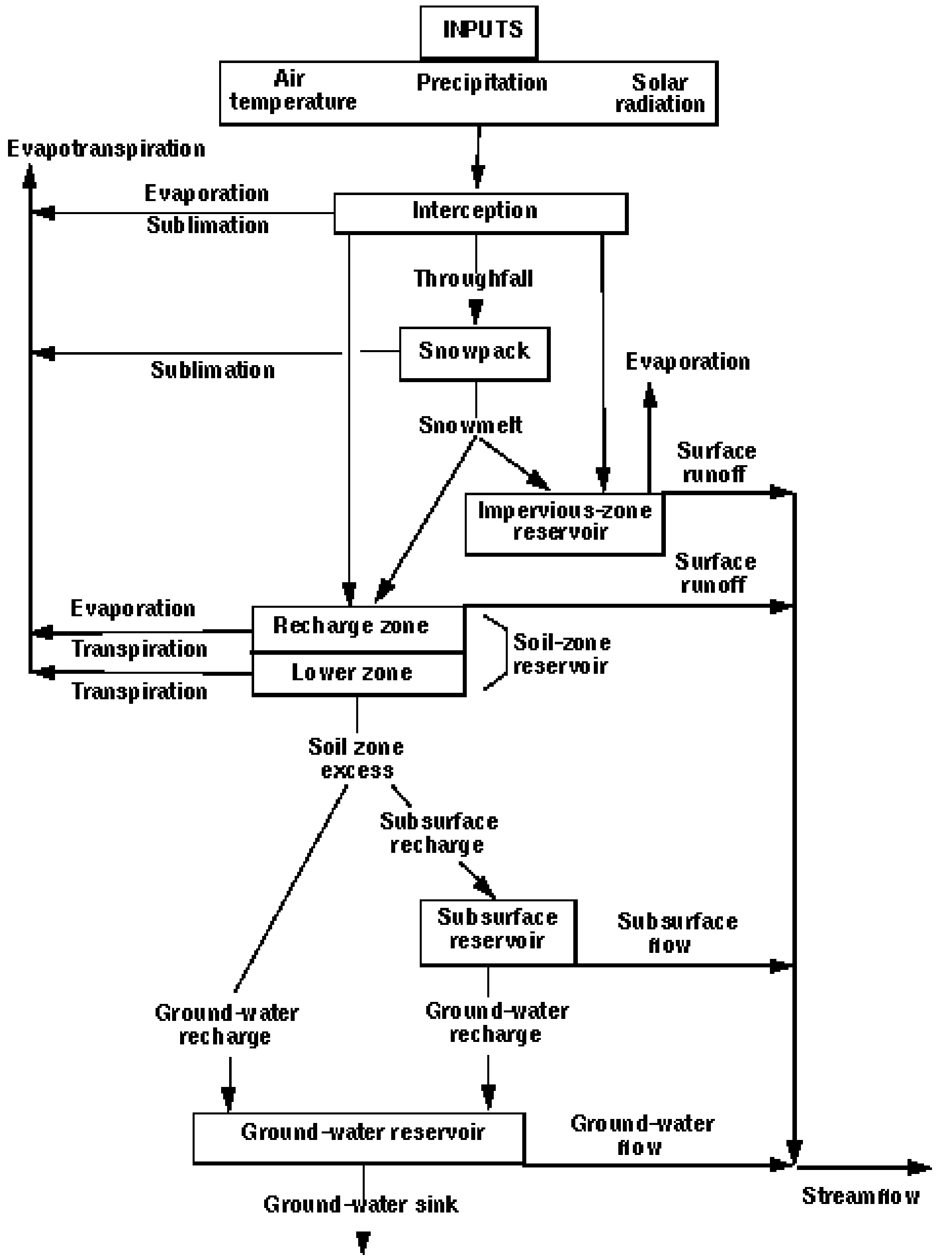
Precipitation Runoff Modeling System (PRMS)

[distributed –parameter, physically-based watershed model]

Implemented in:

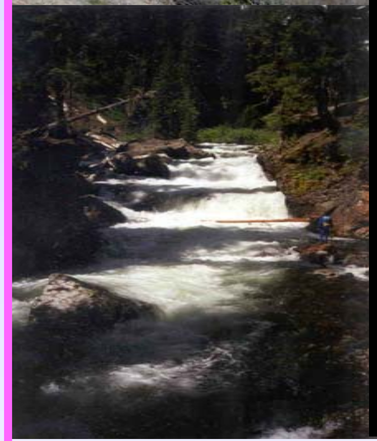
The Modular Modeling System (MMS)

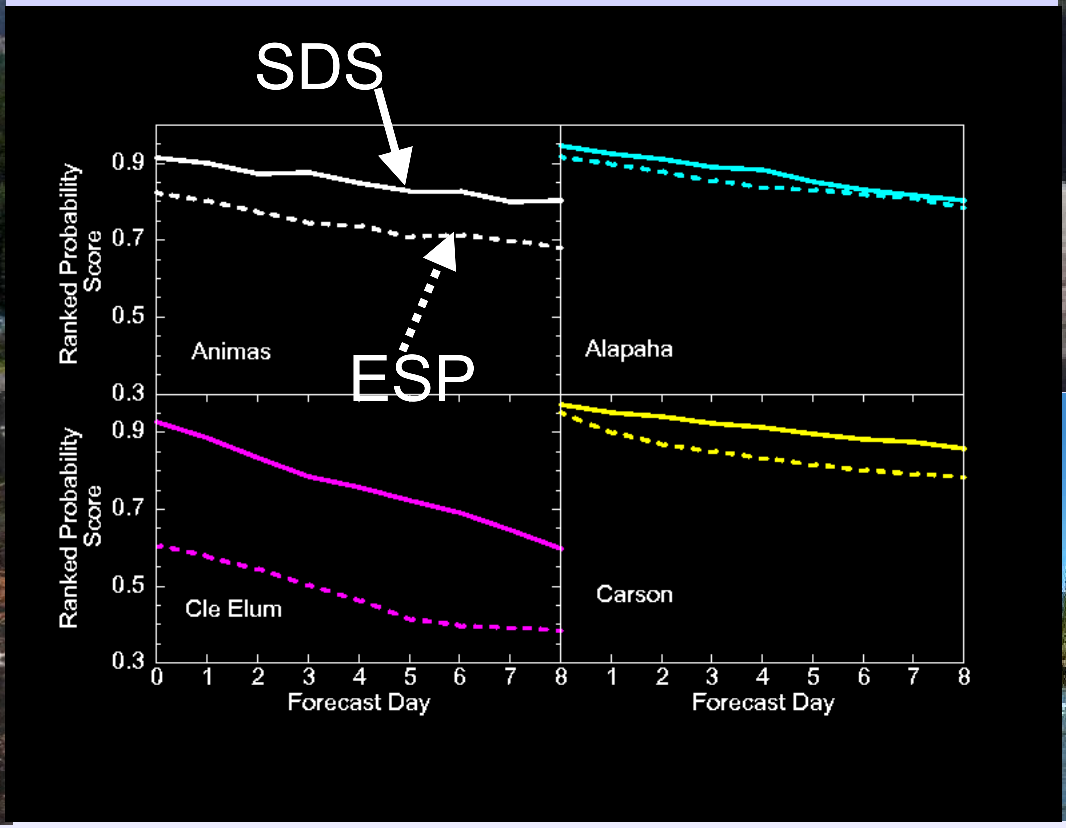
[A set of modeling tools to enable a user to selectively couple the most appropriate algorithms]

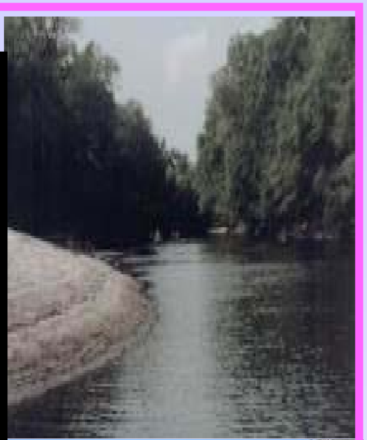


Ranked Probability Score

Measure of probabilistic forecast skill



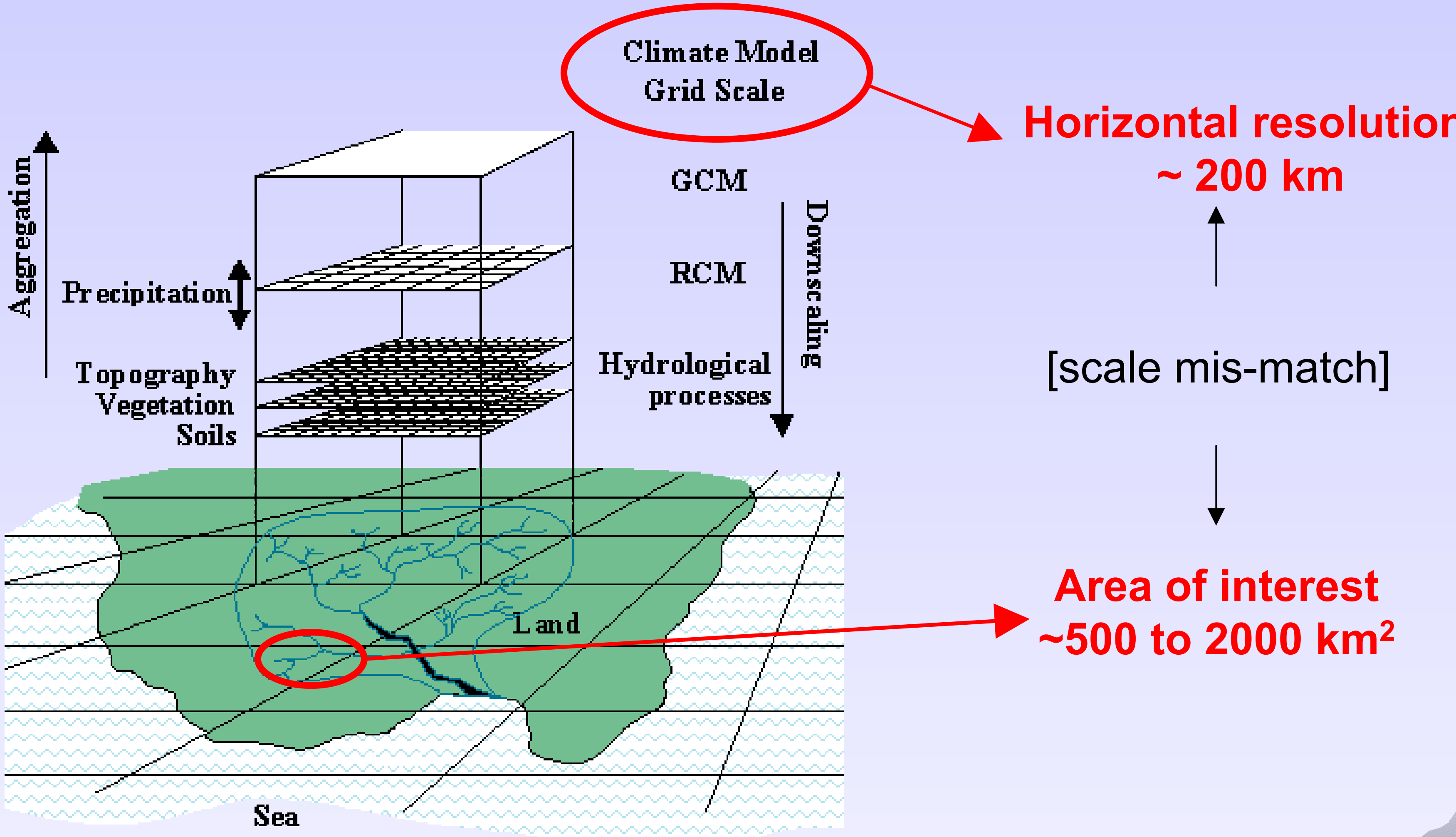




SDS

ESP

Methods for experimental forecasts



- **Purpose: Downscale global-scale atmospheric forecasts to local scales in river basins (e.g., individual stations).**

Downscaling approach

- **Identify outputs from the global-scale Numerical Weather Prediction (NWP) model that are related to precipitation and temperature in the basins of interest**
  - Geo-potential height, wind, and humidity at five pressure levels
  - Various surface flux variables
  - Computed variables such as vorticity advection, stabilitiy indices, etc.
  - Variables lagged to account for temporal phase errors in atmospheric forecasts.

- **Use NWP outputs in a statistical model to estimate precipitation and temperature for the basins**
  - Multiple linear regression
  - Local polynomial regression
  - K-nn
  - Canonical Correlation Analysis
  - Artificial Neural Networks
  - NWS bias-correction methodology

Multiple linear regression approach

- Multiple linear Regression with forward selection

  $$Y = a_0 + a_1X1 + a_2X2 + a_3X3 \ldots + a_nXn + e$$

- Use cross-validation procedures for variable selection – typically less than 8 variables are selected for a given equation

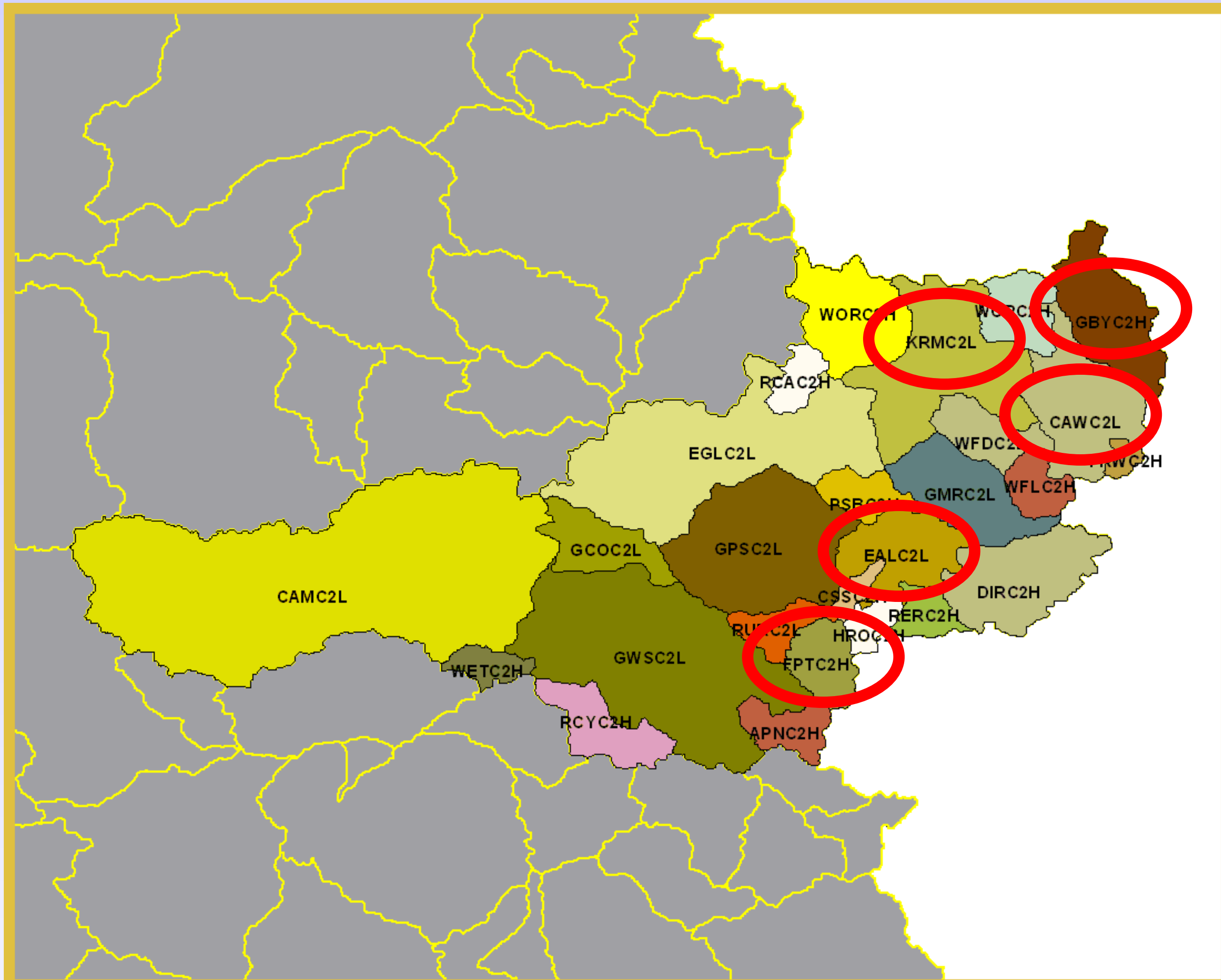
- Stochastic modeling of the residuals in the regression equation to provide ensemble time series

- A separate equation is developed for each station, each forecast lead time, and each month.

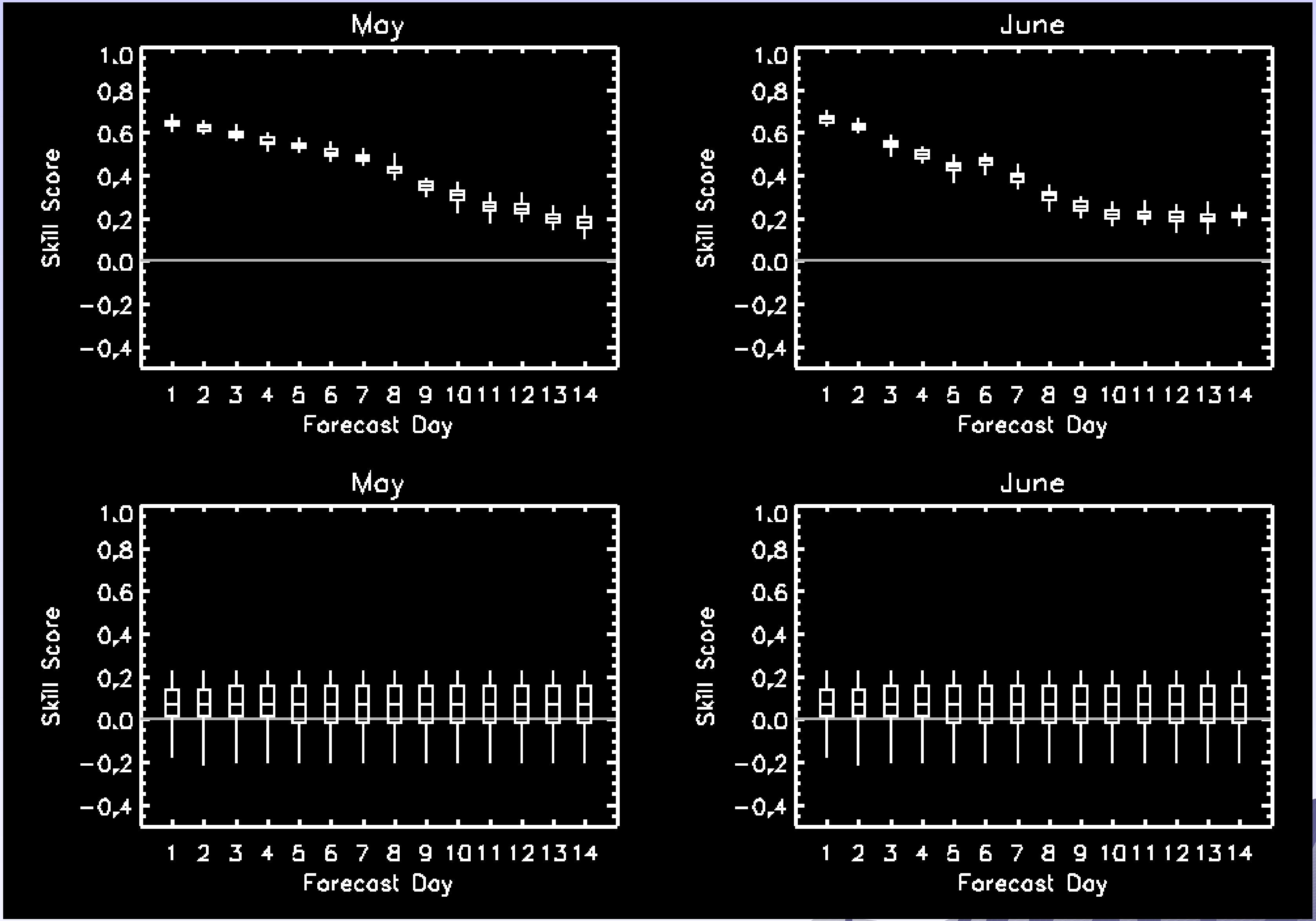
- Regression coefficients estimated for the period of the NWP hindcast (1979-2001) and applied to the CDC experimental forecasts in real-time

- Local-scale precipitation and temperature forecasts are used as input to the CBRFC hydrologic modeling system to provide real-time forecasts of streamflow

Results for example basins

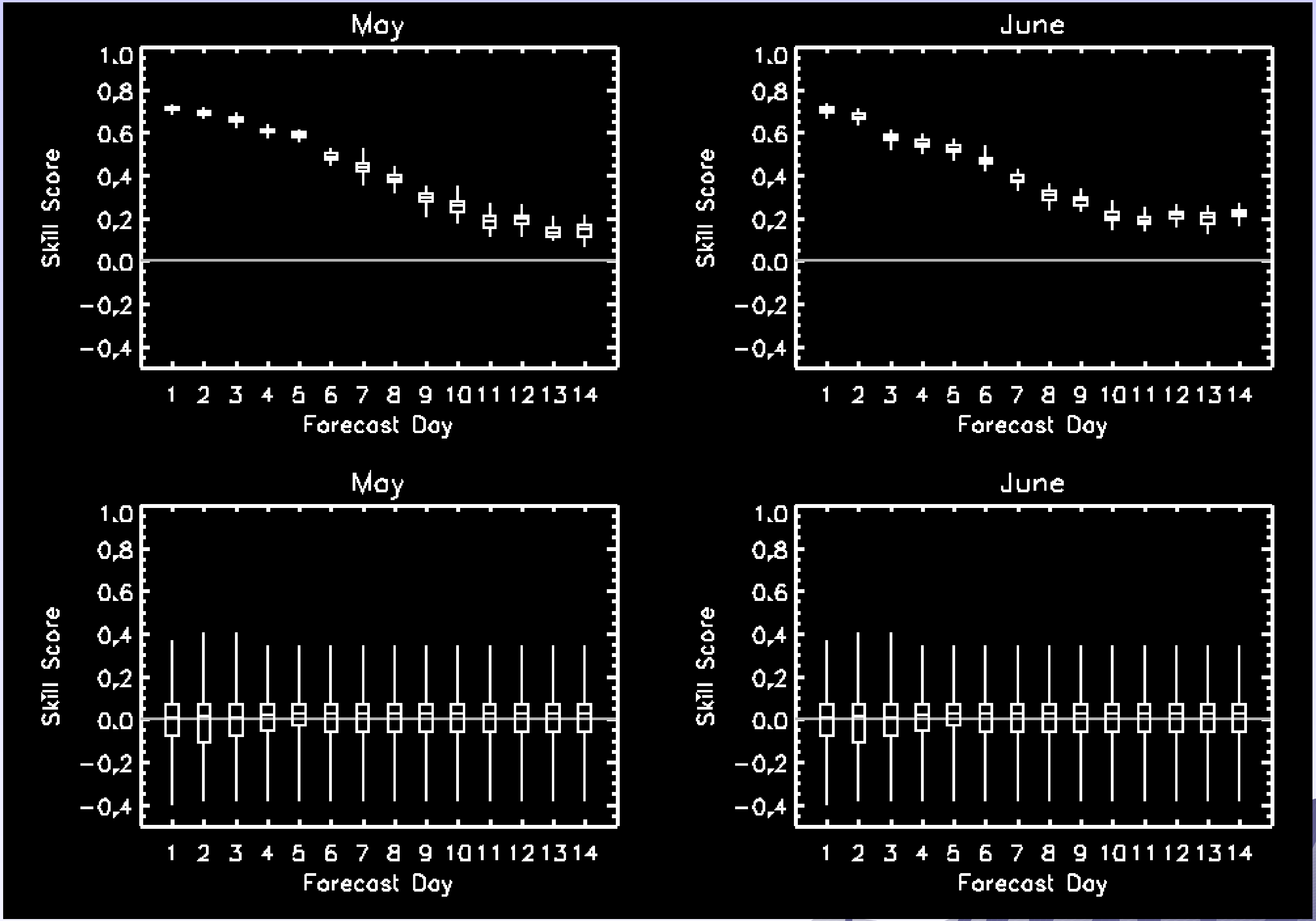


Cawc2llf



May
June
May
June
Skill Score
Forecast Day
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
1 2 3 4 5 6 7 8 9 10 11 12 13 14

Ealc2luf


May
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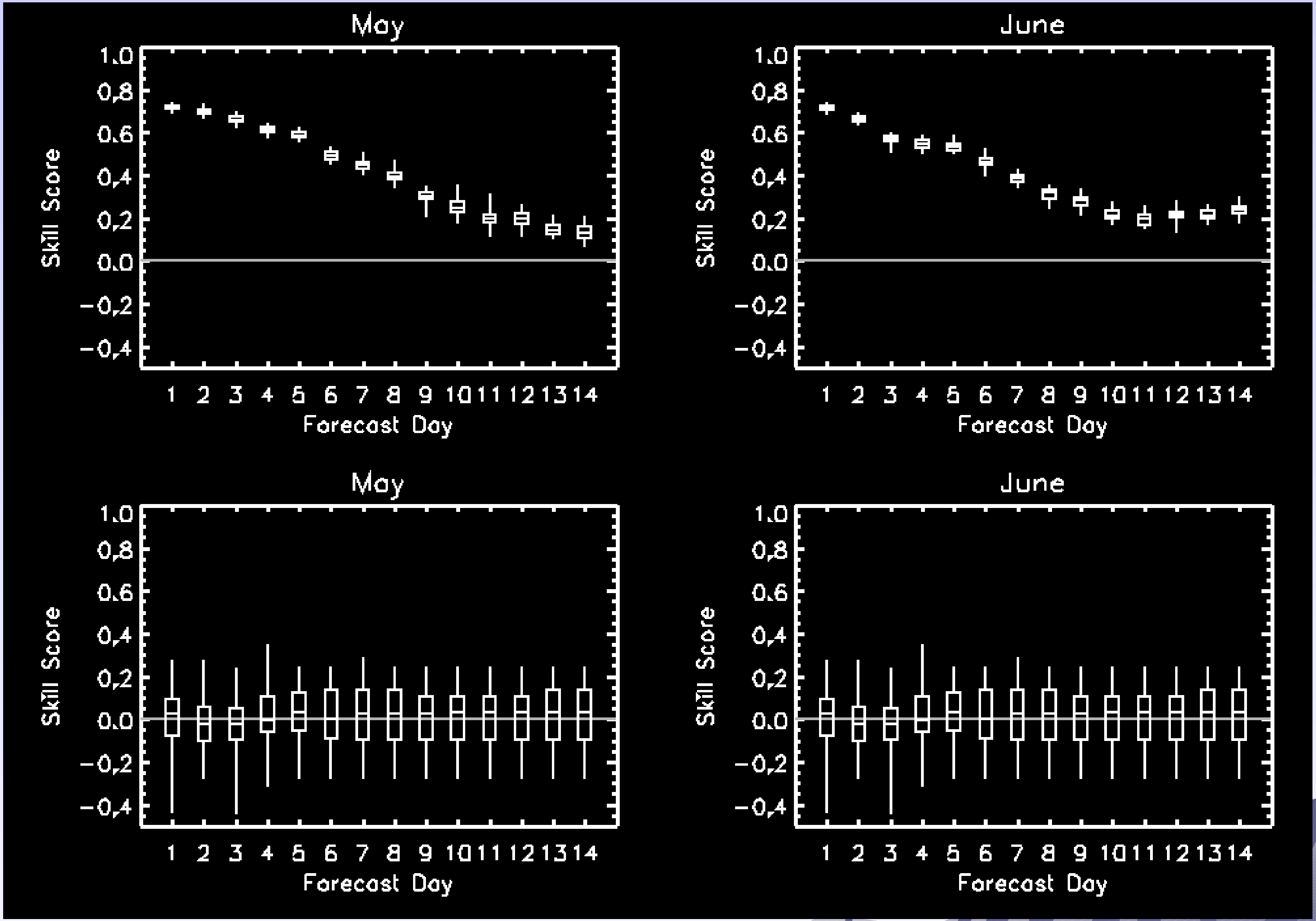
1 2 3 4 5 6 7 8 9 10 11 12 13 14

Fptc2huf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Forecast Day
May
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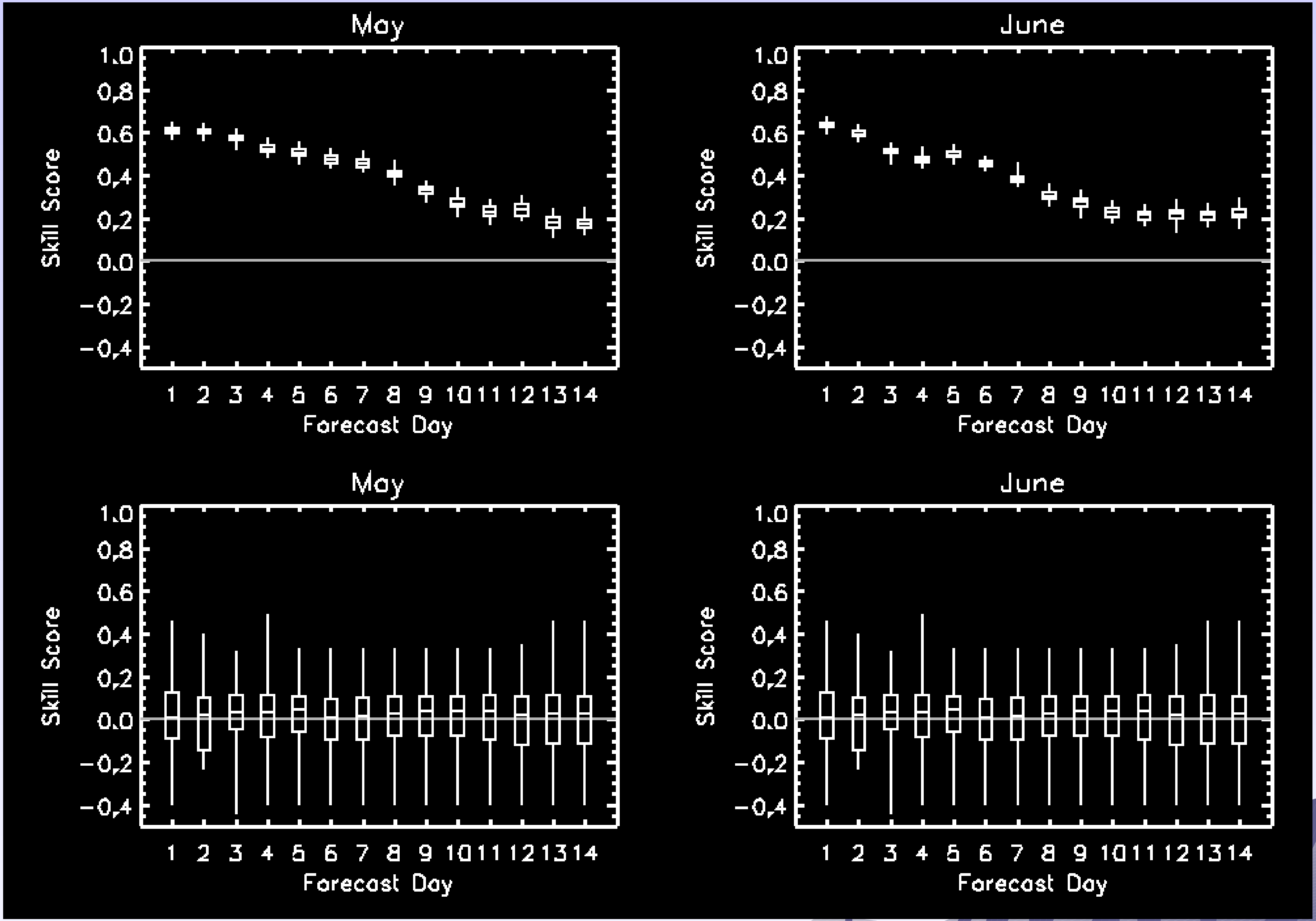
Forecast Day

Gbyc2hmf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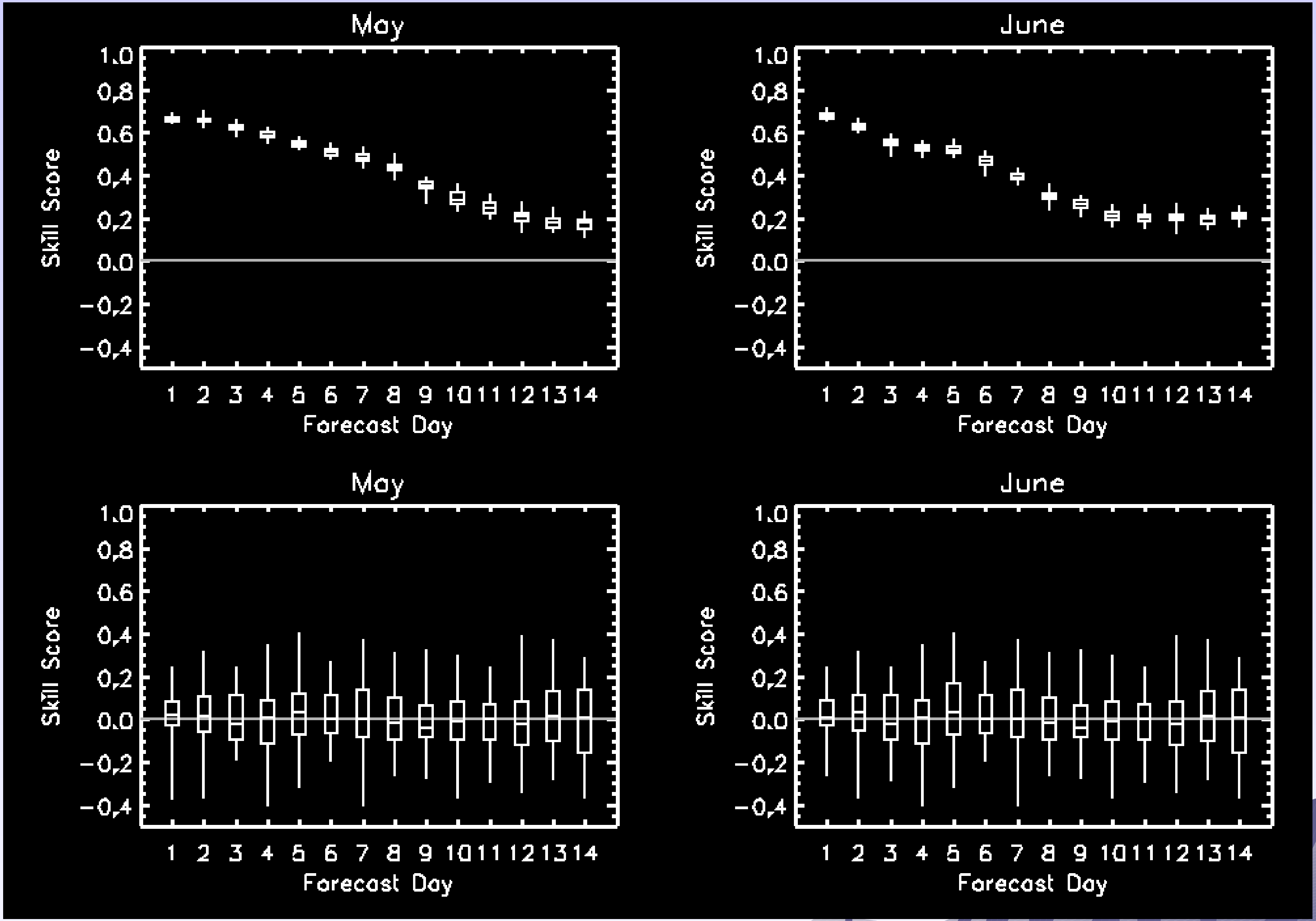
Krmc2llf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Ongoing work

- Implement logistic regression to predict the probability of precipitation occurrence (done)
- Cross-validated MLR results (runs are in progress)
- Comparisons with downscaling to station data (runs are also in progress)
- Estimates of necessary sample size to develop stable regression equations
- Use of pooled regression to increase sample size and preserve spatial co-variability (evaluate possible trade-offs between accuracy at individual stations and the consistency of the spatial fields)
- Implementation of other statistical techniques (K-nn, CCA, ANN, NWS bias correction, etc.)

Impact

- Partnerships with NWS Office of Hydrologic Development and CBRFC to develop state-of-the-art techniques for hydrologic forecasting (through well-documented scientific comparisons)

- Implement these techniques in NWS operations.